Visualising Knowledge Based Systems

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Abstract: Knowledge acquisition and the generation of explanations from rule-based systems continue to be problem areas in knowledge-based systems. The difficulties encountered are often due to the modeling nature of these tasks. Since models are often best represented diagrammatically it seems reasonable to use approaches that visualise the rules in a knowledge-based system. Visualisation can be used to assist the expert in understanding better the models underlying the knowledge being captured and to act as a communication channel between the domain expert and the knowledge engineer.

An approach has been developed that rapidly and incrementally acquires rules in a textual form using cases in conjunction with Ripple Down Rules and retrospectively produces a conceptual lattice using Formal Concept Analysis. This paper focuses on the value of the concept lattice as a modelling aid. A number of aspects of the concept lattice are evaluated including the general applicability of using FCA to analyse rule-bases, how the representation compares to other knowledge representations, how easily the representation is understood and how well the representation can be used for learning. A survey is reported which shows that the FCA line diagram is an acceptable representation that can be learnt quickly and used for understanding the contents, and particularly the structure, of a knowledge based system.

Keywords: Knowledge-based systems, conceptual modelling, ripple-down rules, formal concept analysis

1 Introduction

Knowledge acquisition and the generation of explanations from rule-based systems continue to be problem areas in knowledge-based systems (KBS). The difficulties encountered are often due to the modeling nature of these tasks. Since models are often best represented diagrammatically it seems reasonable to use approaches that visualise the rules in a knowledge based system. Such an approach can be used to assist the expert in understanding better the models underlying the knowledge being captured and to act as a communication channel between the expert and the knowledge engineer.

The aim of the work described in this paper was to provide some evaluation of a rule-based modelling tool known as MCRDR/FCA, which combines Multiple Classification Ripple-Down Rule (MCRDR) [8] and Formal Concept Analysis (FCA) [23]. The incorporation of FCA ideas into MCRDR has enabled term subsumption hierarchies (the concept lattice) to be developed from the primitive (and textual) concepts held in an MCRDR KBS. Since many of the claimed features of MCRDR/FCA hinge on the value of the concept lattice, the goal of this paper is to evaluate the usefulness of the FCA concept lattice, also referred to as a line diagram, along a number of dimensions. The first one is generality. The tool has been developed to take as input MCRDR KBS which use an exception structure for knowledge representation, as shown in Figure 5. However, it is claimed that using FCA a T-Box1 can be generated from any A-Box2 that can be converted into a decision table. For a discussion on how the conversion is achieved and an introduction to FCA and MCRDR see [15]. However, the use of FCA extends beyond MCRDR KBS. As an example of how a knowledge representation other than MCRDR can be analysed using FCA, in Section 2 a CLIPS rule-base is converted into a decision table (cross table) and a line diagram produced to describe the knowledge. Section 3 considers a different aspect of generality, by evaluating the FCA line diagram as a taxonomic representation. Section 4 considers whether the line diagram can be seen as a generally acceptable visual representation. To achieve this the FCA diagrams are compared to a number of other graphic representations of the same set of rules. The reader will of course decide which representations they prefer, and why, but some statistics from a survey are given on how well each of these representations scored using a set of four criteria: pleasing appearance, comprehensibility, good structure and ability to determine implications. Section 5 offers some discussion and concludes that the FCA line diagram is a useful visual knowledge modelling technique.

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[1] Terminological KB consist of terms structured into inheritance networks [1]. Their main building blocks are concepts and roles and they reason by determination of subsumption between concepts [11].

[2] Assertional KBS are made up of executable assertions (such as rules) that assert the relationships between terms.

```
1 %BIRDP(backbone=yes);(warm.blooded=yes);(has.breasts=no);
2 %FLATW(backbone=no);(live.prime.in.soil=yes);(flat.bodied=yes);
3 %WORML(backbone=no);(live.prime.in.soil=yes);(flat.bodied=no);
4 %FISH0(backbone=yes);(warm.blooded=no);(always.in.water=yes);(boney=yes)
5 %SHARK(backbone=yes);(warm.blooded=no);(always.in.water=yes);(boney=no);
6 %CMINS(backbone=no);(live.prime.in.soil=no);(body.in.segments=yes)(shell=no);
7 %BAT00(backbone=yes);(warm.blooded=yes);(has.breasts=yes);(can.eat.meat=yes);(fly=yes)
```

Figure 1: An Extract of the Expanded CLIPS Animal KBS.

The format is: rule number, conclusion code starting with a % and a list of rules conditions

2. The Use of FCA to Model different Knowledge Representations

This paper claims that FCA can be used to display concepts in rule-based systems or any representation that can be converted into a decision table. Colomb [3] has proven mathematically that any propositional KBS or decision tree can be mapped into a decision table. Once we have the knowledge as a binary decision table, the mapping from a decision table to a formal context is a direct translation. In this section the viability of applying FCA to KBS representations other than RDR KBS is shown by using a KBS built using a commonly used and available knowledge representation, known as CLIPS. A sample KBS which is supplied with CLIPS version 5.1 has been selected. The KBS has 84-rules and classifies animals.

2.1 The CLIPS Animal KBS

The CLIPS Animal KBS is easily converted into a decision table. Such a conversion requires the expansion or inflation [3] of each rule into its primitive conditions. Conversion of the CLIPS KBS into decision table format KBS required all abstractions to be removed from the original KBS. Each rule shown in Figure 1 represents a set of primitive concepts. A brief description of how higher concepts are found is given in Section 4.

Many interesting views of the animal classification system were found using this data. In Figure 2 the condition HOOVES=YES was selected. In FCA a concept is made up of a set of attributes and the set of objects which share those attributes. In Figure 2 the concepts are shown as small circles and the sub/superconcept relations as lines. Each concept has various intents (the attributes or rule conditions) and extents (the objects or rule number and conclusion) associated with it. The labelling has been reduced for clarity. All intents of a concept β are reached by ascending paths from β and all extents are reached by descending paths from the concept β. We can see that any animals that have hooves are also vertebrates (BACKBONE=YES), mammals (WARM.BLOODED =YES) and (HAS.BREASTS=YES) and herbivores (CAN.EAT.MEAT=NO). We can also see that the number of toes is the next consideration, which is then broken up into various categories such as if they have horns and how many, if they have plating, if they have fleece, if they live in the desert and whether they are domesticated. It is possible to use the diagrams to see what are the relevant features in classifying animals within an area of interest. This brief example has shown how knowledge that can be converted into a decision table can be utilised to develop line diagrams from which a better understanding of the knowledge, the relationships between concepts, the higher level abstractions and the structure of the KBS can be gained.

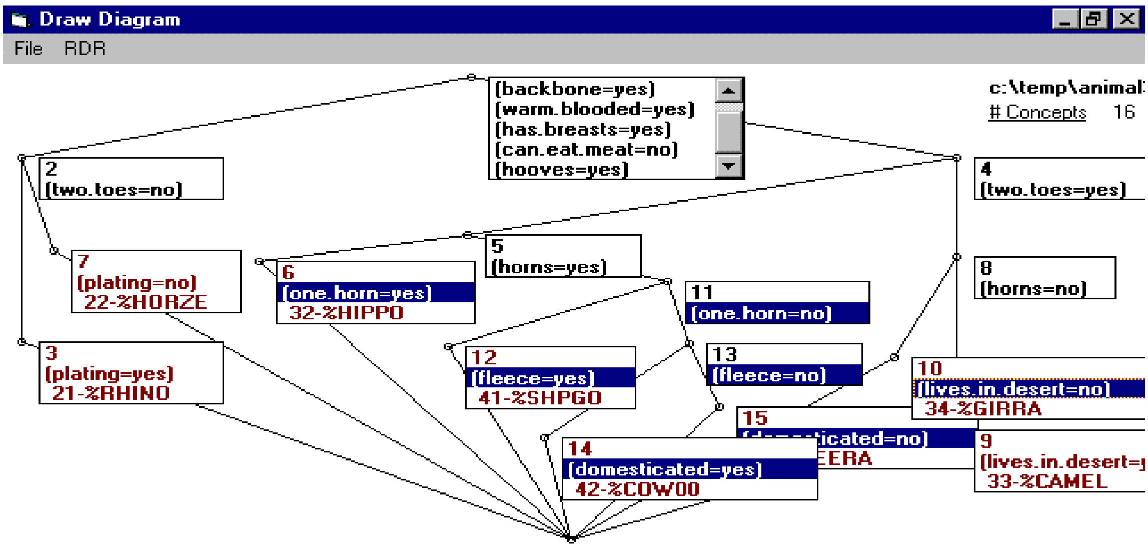

Figure 2: The FCA line diagram for the selection HOOVES=YES in the CLIPS Animal KBS.

3 The Generality of the Visual Representation

In this section we explore the suitability of the FCA line diagram as an ontological and particularly a taxonomic representation. Ontologies are often equated with taxonomies that can be used to classify categories or concept types in a knowledge base [22]. A taxonomy contains a stronger concept of structure and organisation than the word ontology as the word is derived from the Greek taxis and nomos, which respectively mean arrangement and law. Woods [24] notes that: conceptual taxonomies which allow probabilistic and default rules and abstract and partial definitions may be "useful for indexing and organising information and for managing the resolution of conflicting defaults" [24,p.45]. Taxonomies include a classification system which provides the structure that allows new concepts to be positioned appropriately. In the FCA framework, any new concept may be located based on the description of its intent and extent, the attributes and objects that describe the concept. In the MCRDR/FCA framework the taxonomy is recreated each time from the specified formal context and each individual concept is ordered in relation to each other concept. Limited default reasoning is supported in the line diagram through the inheritance of properties (attributes) but the use of roles for default reasoning is not well supported as there are not different links or arcs for different types of relationships between concepts. The line diagram can be described as a concept map with typed nodes but untyped arcs that is a hybrid system which includes a spatial layout and location system, node based system and a link-based system [9, 10].

The line diagram is a complete lattice. Woods remarks that lattices offer "expressive power and the detection and resolution of conflicts in inherited information" [24, p.80] that otherwise might not have been discovered until runtime. The concept lattice also satisfies the informal definition of a semantic net given by Shapiro [18, p.137] as a "labelled directed acyclic graph (DAG) in which nodes represent entities and labelled arcs represent binary relations between entities". The line diagram in FCA is a labelled DAG although the arcs are not labelled but can be read as a binary relation which means "isa" when traversing the graph from bottom to top for extensions. Nets also provide "clustering of properties around concepts and the incorporation of inheritance hierarchies" [17,p.102] and inference propagation. Each of these features are supported by the FCA line diagram. Woods [24] sees semantic networks as different to other knowledge representation because of the use of links to record facts and store associations which can be used for reasoning. Schubert, however, points out that many, if not most, knowledge representation are able to provide many of these features and tries to distinguish a semantic net from other representations. He draws the conclusion that semantic nets should not only be graphic taxonomic reasoners but that they should use graph theoretic notions. This point is made again by Shaw and Gaines [19] in the closing quote in this section.

The use of extensional definitions in FCA can be seen as problematic when we come to describe situations for which there are no real examples. However, say that we wanted to compare a horse, zebra and unicorn. There is nothing to stop us describing these three objects in terms of their real or imagined properties in a formal context. FCA is an intensional logic that uses descriptions of the attributes of objects as a means of classifying and ordering objects. Of course, there may be a concept that can not be found in any object, real or hypothetical, and it would not be possible to include this concept in our subsumption hierarchy unless the properties of that concept are contained in the intersections of properties of other examples. Using Cruse's [4] creature taxonomy as an example, it can be seen in Figure 4 that it is necessary to treat the higher level concepts (collie, cat, robin and starling) as examples in order to include them in the taxonomy. Figure 3 shows the KL-ONE-like [2] knowledge structure used to produce the line diagram in Figure 4.

```
1 %cat00 (cat);(animal);(creature)
2 %colli (collie);(dog);(animal); (creature)
3 %robin (robin);(bird);(creature)
4 %starl (starling);(bird); (creature)
5 %charl (Charles);(spaniel);(dog); (animal); (creature)
6 %tweet (Tweetie);(blackbird); (bird); (creature)
```

Figure 3: The knowledge structure used to generate the line diagram in Figure 4.

Shaw and Gaines [19] have used their visual language to acquire and represent the Cruse creature taxonomy. The diagram they draw is very similar to the FCA concept lattice in Figure 4. The key difference is that they need to perform the modelling up front and draw the diagram first from which a much more lengthy but equivalent KL-ONE like knowledge structure is developed. An example of their visual language is shown in Figure 8. The similarity to and strength of the visual language and the line diagrams over Cruse's representation is well summarised by the quote below:

At one level they are isomorphic visual representations of a taxonomic structure. At another level, the computational representation has the added feature that the underlying data structure exists within the computer and hence is readily subject to graph-theoretic analyses of its fine structure. At another level, it is also an operational knowledge structure within the computer supporting automated deductive inference. At another level, this knowledge structure is available for composition with other knowledge structures to provide a knowledge-based system suitable for testing theories and supporting practical applications. [19,p. 12].

In the next subsection we expand the comparison beyond taxonomic representations to a number of other graphic representations of the same knowledge. The focus is more on the acceptability and usefulness of the representation for human reasoning.

4. Various representations of Cendrowska's Lens Data

The line diagram is seen as a useful representation for understanding the contents of a rule-base. In this section we evaluate this claim and consider a number of visual representations of the same set of rules and their various merits. We consider such things as clarity and the ability to determine implications as well as the ability to show relationships between concepts and the knowledge structure. The discussion is kept to a minimum as the results of a survey, described at the end of this section, act as a good summary of the author's intuitions of these various representations. The five representations are: an MCRDR KBS (Figure 5), a formal context or crosstable (Figure 6), a line diagram (Figure 7), Gaines and Shaw's [7] visual language (Figure 8) and Gaines' Exception Directed Acyclic Graph (EDAG) (Figure 9). Rules for Cendrowska's lens data are used in all diagrams for consistency. Each diagram is shown together with a brief description of its considered strengths and weaknesses.

The MCRDR KBS in Figure 5shows the exception structure of the representation. An added feature of the MCRDR KBS is the storage of cases (referred to in the diagram as corners) associated with each rule which is a valuable aid in providing the context in which the rule applies as well as an aid in KBS maintenance. While the format of the diagram shown is only one possible way that the MCRDR structure can be visually represented, the diagram is adequate since it displays the key aspects that need to be shown which are the exception structure and the associated cases.

In Figure 6 the rule pathways in Figure 5 have been flattened into a formal context. The formal context, or crosstable, provides the benefits of a decision table structure. Each rule can be compared using the same features and in the case of rule bases that use intermediate conclusions the decision table format results in a normalisation of the data to the same level. Decision tables are also a useful format for further processing by a large number of techniques.

The data/rules in the crosstable may be transformed into a concept matrix by using FCA to find the higher level concepts represented in the intersections of sets of attributes and the sets of objects that share them. The concepts in the concept matrix can be ordered using the subsumption relation ≥ and drawn as a complete lattice as shown in Figure 7. The main strengths of the concept lattice is the ability to see higher level concepts from the primitive rule concepts and the structuring of the concepts into a subsumption hierarchy.

The main strength of the combined MCRDR and FCA approach is that the primitive knowledge is easily acquired using cases and MCRDR. Knowledge acquisition using MCRDR is designed to be performed incrementally and on-line while the system is in routine use. The user is responsible for acquiring and maintaining the knowledge. The lattice is regenerated automatically from the knowledge base and thus will be updated when regenerated.

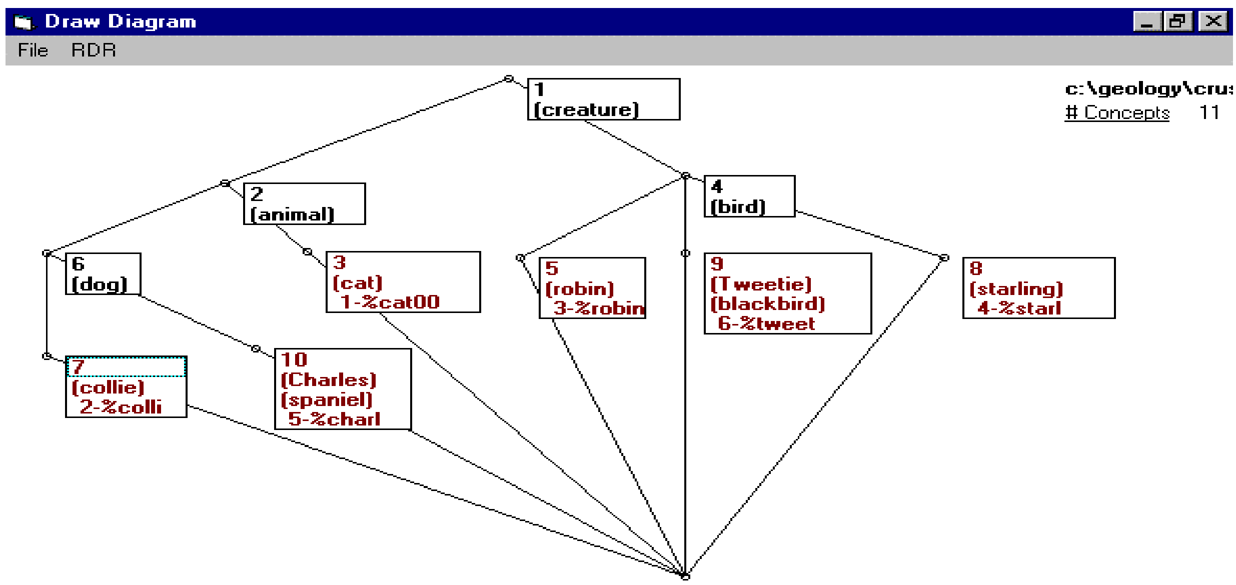

Figure 4: A line diagram to represent the creature taxonomy expanded in the visual language in Fig. 3.

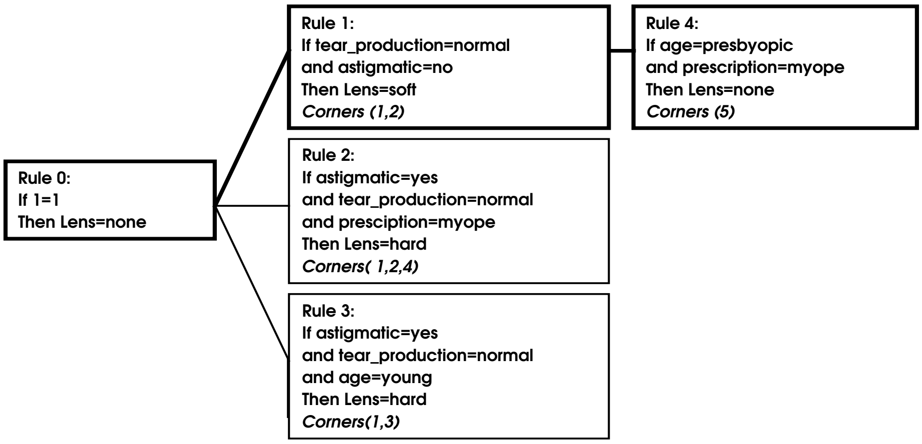

Figure 5. An MCRDR KBS for the Contact Lens Prescription Domain.

The highlighted boxes represent rules that are satisfied for the case {age=presbyopic, prescription=myope, astigmatic=no, tear_production=normal}. The classification given is Lens=none. As this domain only deals with mutually exclusive conclusions we only get one conclusion, but if the domain was extended to cover spectacles and bifocals then this case could lead to multiple conclusions being given.

	1=1[1]	astigmatic = no	tear_prodn = normal	age = presbyopic	prescripton = myope	astigmatic = yes	age = young
1-%LENSN	X						
2-%LENSS	X	X	X				
3-%LENSN	X	X	X	X	X		
4-%LENSH	X		X		X	X	
5-%LENSH	X		X			X	X

Figure 6: Context of "MCRDR Contact Lens Rules"

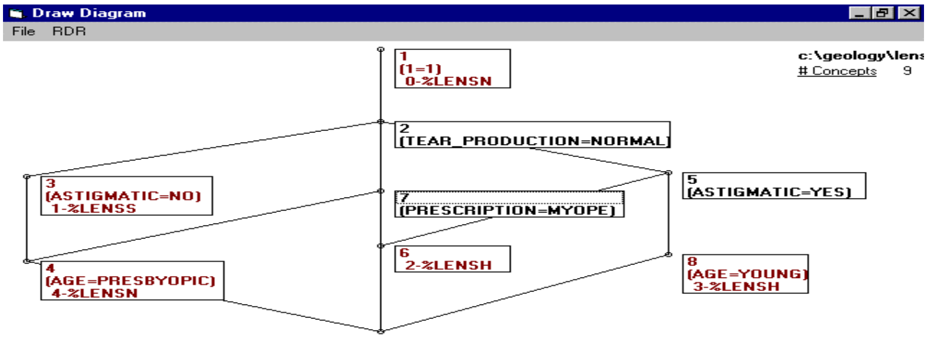

Figure 7: The Diagram Screen in MCRDR/FCA which shows the Concept Lattice for the Formal Context of the MCRDR Contact Lens Rules" given in Figure 6.

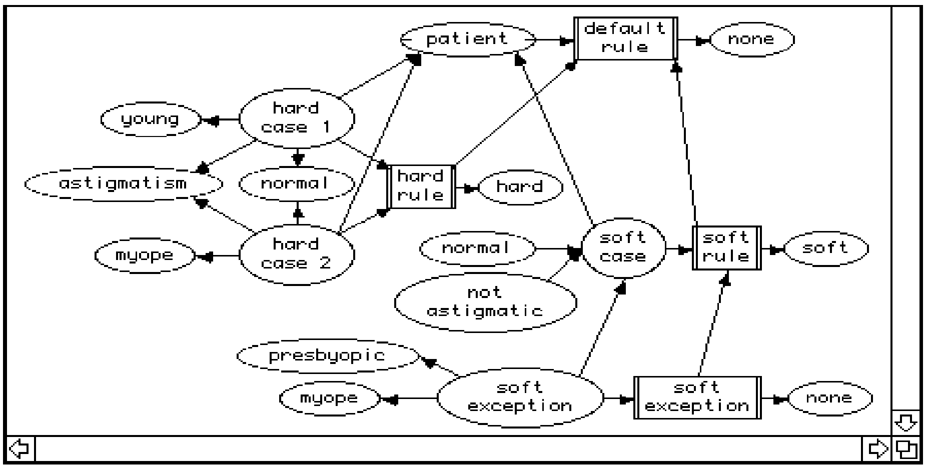

Figure 8 Contact Lens Rules Represented in the Visual Language [7]

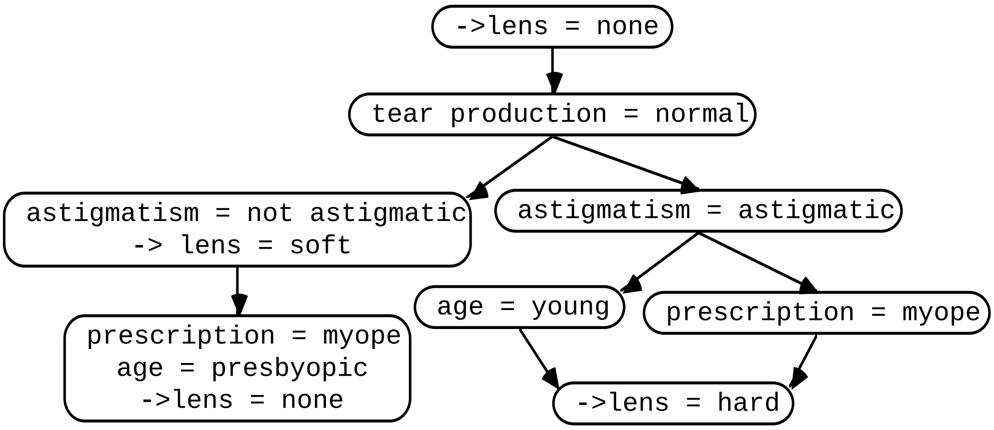

Figure 9 Induct rules with exceptions, factored as EDAG (Taken from [6])

As can be seen in Figure 8, the visual language of Gaines and Shaw [7] offers a graphic representation of the subsume and disjoint logical relations. The visual language provides a domain model that is not present in the other representations and shows how the rules fit into the model. This provides a rich representation but as to be expected as you add more information the diagram becomes more complex compared to the other diagrams.

The final diagram to be compared is Gaines' [6] Exception Directed Acyclic Graphs (EDAGS). The similarity between the MCRDR/FCA diagram and the EDAG in Figures 11 and 12, respectively, warrant a more in depth discussion of the EDAG and how they compare to the FCA line diagram.

The development of the EDAG was motivated by the desire to develop knowledge representations that encode knowledge in a similar way to the expert (Gaines 1991) and to make knowledge comprehensible (Gaines 1996). In support of the views of Michie and Quinlan, Gaines proposes that:

"an excellent performance system necessarily implies the existence of a comprehensible knowledge structure" [6,p. 206].

Compactness, coherence of the structure and the use of familiar concepts are all relevant when determining comprehensibility [6]. Gaines considers the use of default reasoning and rules with exceptions to be a closer representation to the way experts reason than decision trees or production rules. As described in [6], by generalising parts of the tree or generalising rules with exceptions more compact knowledge structures can be developed. In the case of a tree representation, generalisation into partial orders results in branches rejoining and avoids the replication of sub-trees. The similarity with RDR is noted by Gaines with the difference identified as the inability of the RDR structure to allow multiple conclusions. This difference, however, does not exist with the newer MCRDR representation.

In summary, the concept lattice and the EDAG are similar representations, with the concept lattice providing not only the inference paths but also an extensional definition as does the visual language in Figure 8. The MCRDR rule structure provides the inference paths more clearly, shows the cases associated with each rule and is the simplest representation but does not contain any of the higher-level concepts shown in Figure 8, which is the most complex diagram.

To evaluate my findings of the various strengths of these representations 12 computer science and engineering students and academics completed a survey of these six representations. The line diagrams were also evaluated by the subjects from a number of other perspectives which are mentioned in Section 6. The five different representations of the rules which cover Cendrowska's lens data, shown in Figures 5-9, were shown to the subjects using an overhead projector. A brief description of how to read each diagram was given as each diagram was shown on the overhead projector. The averaged score for each diagram using each evaluation criteria is shown in Table 1. An overall rating is given which is the sum of the averaged scores. Using the overall score, the diagrams in order of preference are the EDAG, the MCRDR, the line diagram, Gaines and Shaw's Visual language and the crosstable. It is noteworthy that the line diagram scored the highest for structure, which has been its claimed strength.

	MCRDR	Cross-table	Line Diag	Visual Lang.	EDAG
Pleasing appearance	3.45	2.18	3.45	2.80	4:00
Comprehensibility	3.80	2.60	3.18	2.27	4:09
Good Structure	3.66	3.20	3.88	3.10	3.77
Determine Implications	4.20	2.55	3.44	2.66	4:00
	15.11	10.45	13.95	10.83	15.86

Table 1: The combined averaged results for the 11 subjects.

5. Discussion and Conclusion

A comprehensive discussion on the use and value of visual languages and representations is offered in [9]. Kremer [9] remarks that visual representations have been found to offer noteworthy advantages over linear textual representations. He cites [12] who have found semantic networks to be more “computationally efficient” (comprehensible) than predicate logic. Visual representations have also been useful for visual programming, decision making, knowledge representation, database queries and more. Even the use of indentation in programs has been found to be an important aid in program comprehensibility [20]. The survey mentioned in the previous section showed that graphical representations are not always easy to understand and can be considered an “acquired skill” [13]. Although Petre and Green found that the subjects in their study could use the textual representations more quickly they also found that the graphical representations offered a much richer representation once the subjects had passed through the learning curve. Kremer [9] lists the arguments of [20] which describe the psychological benefits of visual languages for programs and data.

These arguments include:

- abstract reasoning is pictorial and thought may involve manipulation of images,
- linear verbal language only provides one dimension but visual reasoning uses two or three dimensions;
- visual images assist “chunking” and short-term memory and
- images tend to be analogical.

Charles Sanders Peirce who developed the a visual logic language known as existential graphs on which Sowa [21] based his Conceptual Graphs states:

"I do not think I ever reflect in words: I employ visual diagrams, firstly because this way of thinking is my natural language of self-communion, and secondly, because I am convinced that it is the best system for the purpose [Ms 620, p. 8] [16, p.126].

Kremer [9] also makes the point that to date there is little hard evidence of the benefit of visual representations and that most interest is due to an intuitive belief that visual representations offer many benefits over textual or linear representations. The survey mentioned in Section 5 sought to evaluate a number of aspects of the line diagram including: how easy it was to learn to read the line diagram; the value of the line diagram representation over a linear textual rule trace; and how well the diagram could be used for learning about a domain and the knowledge in a KBS. The survey found that 10 out of the 12 subjects were able to learn to read a line diagram within a few minutes, that the line diagram was easier and faster to use than a rule trace in answering questions about the knowledge base and that even novices could reason about the knowledge using the line diagram allowing the tool to be used for such purposes as hypothesis testing and tutoring. The results were promising but, as noted by [9] and evidenced in [13]'s study, use of a visual language requires time and effort to learn and this makes evaluation of the line diagram by novices a difficult task. A different type of evaluation has also been undertaken with experts from four different domains who were asked to comment on the observations made by a novice from looking at line diagrams developed from KBS for their domain. The results indicated that the novice had gained an understanding of the key concepts in each domain and that the line diagrams were useful for motivating discussion between the novice and the expert and for identifying missing and erroneous knowledge on the part of the student. The results of the survey with novices and the evaluation with domain experts is not conclusive or large enough to allow statistical sampling. However, as a preliminary evaluation the results are promising. A detailed description and discussion of the survey with novices and case studies with experts is given in [14].

In this paper the value of the FCA line diagram has been considered. It has been shown that knowledge converted into a binary crosstable can be used as input into MCRDR/FCA and used to develop line diagrams. The layout of the line diagrams are very simple and could be improved with other layout algorithms. Further enhancements to the interface are necessary to support features such as scrolling, zooming, hiding or expanding nodes. It is also planned that a number of layout algorithms be made available to further assist in exploration of the knowledge from different perspectives. At this stage all changes are made to the knoweldge base which are then reflected in the lattices generated. It would be nice to be able to modify the knowledge via the lattice but since the view would generally be a subset of the entire knowledge base it is difficult to determine how such changes should be propagated. Even in its current form the FCA line diagram was found to be a representation that is generally useful for analysing rule-bases and comparable to other visual knowledge represenation. The use of FCA allows the structure of the knowledge to be found and displayed as a term subsumption hierarchy which is useful for such purposes as explanation and teaching. The most interesting feature of this work is that the FCA terminological KBS is generated automatically from an assertional KBS. This suggests that we do not need to start with building complex domain models before we can begin the capture of assertions. Since models are unreliable and imprecise it may be preferable to use a technique such as MCRDR which offers a simple and reliable knowledge acquisition, maintenance and validation methodology to acquire a performance system and employ FCA to generate an explanation system without the typical problems associated with the KA bottleneck.

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