Legal Knowledge Based Systems

JURIX'96

Foundations of legal knowledge systems

The Foundation for Legal Knowledge Systems

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Automating legal reasoning in discretionary domains 101-110
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Paper version: Tilburg University Press, ISBN 90-361-9657-4, NUGI 699

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AUTOMATING LEGAL REASONING IN DISCRETIONARY DOMAINS

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Abstract

Few automated legal reasoning systems have been developed in domains of law in which a judicial decision maker has extensive discretion in the exercise of his or her powers. Discretionary domains challenge existing artificial intelligence paradigms because models of judicial reasoning are difficult, if not impossible to specify. We argue that judicial discretion adds to the characterisation of law as open textured in a way which has not been addressed by artificial intelligence and law researchers in depth. We demonstrate that systems for reasoning with this form of open texture can be built by integrating rule sets with neural networks trained with data collected from standard past cases. The obstacles to this approach include difficulties in generating explanations once conclusions have been inferred, difficulties associated with the collection of sufficient data from past cases and difficulties associated with integrating two vastly different paradigms. A knowledge representation scheme based on the structure of arguments proposed by Toulmin has been used to overcome these obstacles. The system, known as Split Up predicts judicial decisions in property proceedings within Family Law of Australia. Predictions from the system have been compared to predictions from ten lawyers with favourable results.

1 Introduction

Few legal reasoning systems have been developed in domains in which a judicial decision maker has some discretion. (Edwards and Huntley, 1992) applied rule based reasoning to the discretionary domain of Family Law in Scotland and reported some inadequacies of that approach. Our own early work applying rule based reasoning to property decisions in Australian family law also encountered similar difficulties because of the discretionary nature of that domain (Stranieri and Zeleznikow, 1992). The principal statute governing family law, the Family Law Act (1975) of Australia makes explicit a number of factors that must be taken into account by a judge in altering the property interests of parties to a marriage but is silent on the relative weight of those factors. Different judges may, and do, reach different conclusions even when they agree on facts because each judge assigns different relative weights to factors. This makes the specification of a model of judicial reasoning extremely difficult.

Despite the attention focused on discretion by jurisprudential theorists, the concept of judicial discretion has received little attention from the developers of legal expert systems.[1] In contrast, the concept of open texture has been frequently discussed. (Prakken, 1993) depicts law as open textured because legal reasoning is replete with situations that involve defeasible rules, vague terms or classification ambiguities. We argue that decisions which involve judicial discretion also contribute to the

[1] Most legal theorists accept that some degree of judicial discretion is an inevitable feature of any judiciary. (Hart 1994) assigned judicial discretion a minor role in his jurisprudence compared with critical legal studies (CLS) theorists. (Kennedy 1986) provides an entertaining CLS account of the way in which a fictitious judge exercises discretion to the extent of pre-determining a desired outcome before searching for precedents or statutes that can support the desired outcome. (Dworkin 1967) elucidates distinct types of discretion though (McCormick 1981) advocates discretion is a matter of degree and not of type.

characterisation of law as open textured. However the judicial discretion is apparent in straightforward cases in family law is not an instance of defeasible rules, vague terms or classification ambiguities but is a distinct type of open texture.

Judicial discretion in family law is best seen as a different type of situation that is characterised as open textured. Consider a hypothetical panel of Family Court judges who agree on all the facts of a divorce. Members of the panel can conceivably arrive at different percentages of the assets that ought to be awarded to the wife (and husband). Divergent interpretations may be due to the presence of vague terms interpreted differently by different judges or they may be the result of classification type anomalies. One judge classifies a lottery win as a contribution to the marriage whereas another does not. Different outcomes may even be the result of defeasible rules. One judge applies the principle known as the "*asset by asset*" approach whereas another considers that principle irrelevant and adopts the "*global*" approach. While these scenarios describe situations that are accepted as open textured, there is another situation, common in family law cases that is not captured by these instances of open texture.

A panel can be imagined where vague terms are interpreted in much the same way by all judges. There are no classification anomalies and the same principles have been used by all judges. In this scenario, outcomes may still be different because judges apply different weights to each relevant factor. Thus, an additional situation is apparent; one where the decision maker is free to assign weights to relevant factors, or combine relevant factors in a manner that is his own choosing. This will certainly contribute to the open textured nature of law and contribute to indeterminacy.

Ascertaining knowledge about how a decision maker weights and combines factors from experts by direct interview is difficult in that a guessed numerical weighting is unlikely to represent the actual weight of the factor in the context of a large number of other interdependent factors. However, a record of the way factors have, in practice been combined by judicial decision makers exists in the form of a transcript of judgements made by them in typical cases. Knowledge about decision making patterns can be induced from data from a sufficiently large numbers of these cases.

We have collected data from large numbers of family law cases and then applied neural network algorithms to learn the relative weighting of each factor across all cases. We believe the connectionist paradigm is well suited to reasoning in discretionary domains because the elicitation of a domain model is not required nor attempted as machine learning algorithms are used only to learn patterns of decisions from past cases.

Significant obstacles hinder the use of connectionist methods to legal reasoning. As (Bench-Capon, 1993) points out, neural networks require very large training sets of quality data. Often data sets representing thousands of past cases are simply not available. We have overcome this problem by decomposing the reasoning into a number of smaller units. Each small unit is implemented with a small neural network which requires far fewer training examples than a larger network. We use rule sets derived from expert heuristics for those units where data was either unavailable or not sufficiently reliable for neural network training. Decomposing the task into small units, where each unit is implemented using a neural network or a rule set is conceptually straight forward, however performing the decomposition in a manner which is methodical is a significant obstacle. A further obstacle to this approach relates to the generation of explanations.

The connectionist paradigm is very poor at generating an explanation for conclusions inferred. However, we take the view that the rule based paradigm is also unable to generate a useful explanation. A rule trace explanation generated from rule based reasoning is typically too detailed to be useful as an explanation. The assumption we have made in Split - Up is that an outcome is inferred with the use of a number of neural network and rules which are interconnected. Once complete, an explanation may be generated by a process quite independent of the processes used to infer the outcome. Thus, the explanation is not directly related to the method used to generate a conclusion. This approach draws jurisprudential support from the movement broadly known as legal realism.

The legal realism movement exemplified by (Llewellyn, 1962) is less concerned with legal doctrine than with observation of the law in process. Llewellyn assigns rules and principles a different status than is the case in positivist schools. For positivist schools, rules, principles and standards determine a judicial decision. For realists, rules and principles may be invoked after a decision has been reached in order to ensure that a decision is just, moral and legally correct.[2]

The problems inherent in explaining inferences and in decomposing tasks are resolved in the Split Up system with the use of a knowledge representation frame based on the argumentation theory of (Toulmin, 1958). Argumentation has been used by us to structure family law knowledge so that rule based reasoning and neural networks can be integrated into one seamless system. The argumentation representation enables meaningful explanations to be generated and also enables the task of determining the percentage split of assets to award each party of a failed marriage to be broken down into sub tasks small enough to be implemented with very small neural networks. The argumentation based representation is thus central to our method. We briefly discuss the philosophical basis of argumentation and place our method in the context of related work in artificial intelligence and law

2 Argumentation in artificial intelligence

Over three thousand years ago, Aristotle presented two types of proofs.[3] Dialectic proofs concern opinions that are adhered to with variable intensity. The objective of an exponent of this type of reasoning is to convince or persuade an audience to accept the claims advocated. The second type of proofs are known as analytic proofs. Analytic proofs differ from dialectic proofs in that conclusions are reached by the application of sound inference rules to axioms.

Perelmen and Obtrechts-Tyteca (1969) reflect that modern logic is almost exclusively concerned with analytic proofs. Quite independently, and in the same year those authors and the British philosopher Stephen Toulmin (1958) argued for the resurrection of the Aristotelian dialectics to the same status as that of analytic logic. For Toulmin, dialectics portrays human reasoning processes far more accurately than analytic reasoning. He examined arguments from a variety of domains and concluded that all arguments, regardless of the domain, have a structure which consists of six basic invariants: *claim, data, modality, rebuttal, warrant and backing*. Every argument makes an assertion based on some data.

The assertion of an argument stands as the claim of the argument. Knowing the data and the claim does not necessarily convince us that the claim follows from the data. A mechanism is required to act as a justification for the claim. This justification is known as the warrant. The backing supports the warrant and in a legal argument is typically a reference to a statute or a precedent case.

Argumentation has been used by artificial intelligence researchers in two different ways; to structure knowledge representation and to model dialectical reasoning. Authors that utilise argumentation to model the dialectical nature of argumentation include (Cohen 1995), (Fox 1986), (Poole, 1988), (Prakken, 1993), (Gordon, 1993), (Branting, 1994), (Farley and Freeman, 1995) and (Dung, 1995). Authors that use argumentation models to enhance knowledge representation include (Dick, 1991), (Marshall, 1989), (Clark, 1991), (Johnston *et al.*, 1993), (Bench-Capon *et al.*, 1991) and (Ball, 1994). The argumentation approach adopted in Split - Up falls within this latter group.

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[2] As (Llewellyn 1962 p58) says:
It was assumed that the deductive logic of opinions need by no means be either a description of the process of decision, or an explanation of how the decision had been reached.
[3] Aristotle in *Topics*.

(Dick, 1991, p. 53) suggests that using argumentation structures to model knowledge is more suitable in legal domains than the use of argumentation as the basis of a dialectical reasoning system. She points out that written judgments of law cases are not a transcript of the dialectical arguments presented to the Court during the course of a case. Rather, the ratio decidendi encapsulated in a written judgment is best seen as an argument that a judge makes to support the decision he has reached. Subsequent cases may use that argument (ratio) but never use transcripts of arguments proposed and attacked by either party during the case.

(Dick, 1991) uses conceptual graphs to represent the Toulmin arguments that were made by judges in deciding a number of contract law cases. By so doing she is able to demonstrate sophisticated information retrieval techniques. (Clark, 1991) has developed a group decision support system in the domain of geological test interpretation by enforcing each participating expert to encode their assertions in the form of Toulmin components. The Toulmin structures provide a unifying framework for the diverse knowledge sources so that his system can offer intelligent support. (Marshall, 1989) and (Ball, 1994) have utilised the Toulmin structures to represent legal knowledge. Their systems are essentially hypertext based systems effective because of the simplicity with which complex knowledge can be represented as Toulmin arguments. Our own use of the Toulmin structures differs from the approaches above because our aim has been to decompose the task, to generate explanations and to integrate different AI paradigms. In (Zeleznikow and Stranieri, 1995) we demonstrated the use of a knowledge representation frame based closely on the Toulmin structure. However, the argument structure we have used in this study differs from the structure originally presented by Toulmin and is described below.

3 Split Up description

Split Up has been implemented as an argument based reasoning shell. Family law knowledge has been entered into the shell so that the argument based framework can be evaluated though studies are under way to demonstrate that the shell can also be useful in non legal domains. The knowledge frame used in the current study differs from that proposed by Toulmin in three fundamental ways:

- reasons which explain why a data item is relevant for a claim are explicitly represented. We have called this warrant type 1. (Stranieri and Zeleznikow, 1995) have demonstrated that this is can be used as the basis for the automatic construction of a new argument from two existing arguments that have the same type one warrant.
- reasons that explain why the inference method used is appropriate are explicitly represented. We have called this warrant type 2.
- an inference procedure, algorithm or method used to infer an assertion from datum is explicitly represented.

Figure 1 illustrates the data, claim, two types of warrant and their respective backings; all of which are the components of the argument frame we use. The reason that the data item "The husband has contributed X relative to the wife" is relevant in the *percentage split* argument within Split Up is that Section 79(4) of the Family Law Act specifically obliges a decision maker to take past contributions into account. The hair colour of the judge was considered irrelevant because we could think of no reason that would make this feature relevant. Van Dijk (1989) notes that the notion of relevance has puzzled logicians throughout history and has recently given rise to a class of modal logics broadly described as "relevance logics". One aspect of relevance that van Dijk describes is the requirement that propositions within the same assertion are expected to be relevant to each other. He eliminates a notion of shared concepts or shared referents as the basis for an understanding of relevance and contends that relevance is firmly rooted in the pragmatics of language. We adopt this stance and maintain that a data item is relevant to an argument if a sentence illustrating the reason for the relevance can be uttered.

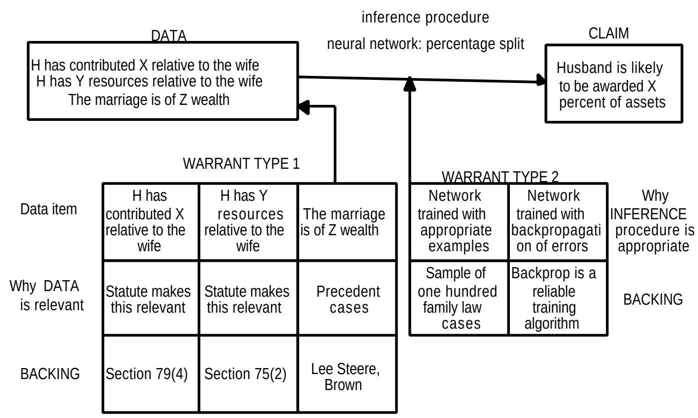

Figure 1: Argument structure used in Split Up

The representation of a reason that explains why an inference procedure is appropriate is a form of warrant that contributes to an explanation of why a claim follows from data. As Figure 1 illustrates, the neural network used in the percentage split argument is appropriate because it has been trained with data from one hundred actual cases. Another reason it is appropriate is that it was trained with the backpropagation of errors learning rule, a method that has been proven to be functional. A reason that the application of a rule is appropriate in other arguments is that the inference is an instance of modus ponens, an inference rule that is demonstrably sound.

Reasoning toward a percentage split of marital property is represented in Split Up as a sequence of arguments. A subset of the arguments is illustrated in Figure 2. The claim of each argument is paraphrased and appears as the rectangle label. The symbols beginning with “s” identify sentences stored in a sentence base and those beginning with “A” identify arguments. The argument in Figure 1 is at the extreme right of Figure 2. Thirty five arguments participate in the reasoning of a percentage split of the assets. Twenty one of the arguments infer a claim value from data values with the use of neural networks, fourteen do so with the use of rule sets.

The argument structure presented in Figure 2 was derived during consultation with our principal domain expert, Renata Alexander, a specialist family lawyer with the Legal Aid Commission of Victoria.[4] To elicit an entire argument structure for the domain, the expert needed only to nominate data items relevant for each claim. No attempt is made to detail how the claim for an argument might actually be inferred from the specified data elements. Thus, eliciting an entire argument structure from an expert is not a time consuming or laborious task.

During a consultation the user is prompted to supply facts which are data items for arguments at the extreme left of Figure 2. The inference method associated with each argument is invoked in order to produce an assertion value which is fed in to arguments further along the hierarchy as data values until a final claim is produced. The final claim advocates a percentage split of the marital assets. Once this has occurred, the user is able

[4] Legal Aid Commission of Victoria is government funded agency committed to the provision of legal services to low income clients.

to invoke the warrants and backings of arguments back down the hierarchy, as explanation.

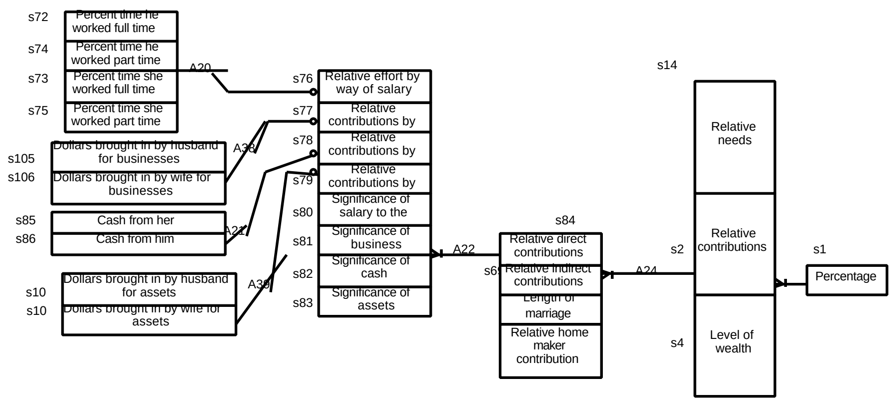

Figure 2: Ten of the arguments in Split Up

3.1 Neural networks in Split Up

The argument structure depicted in Figure 2 served as a template for the collection of data from actual cases. We had access to four hundred family law cases stored within the Melbourne registry of the Family Court of Australia. However, a large number of these cases involved custody issues in addition to property and could not be used because expert opinion indicated that property proceedings are certainly influenced by custody matters. One hundred and three cases involved only property. Two raters extracted data from these cases by reading the text of the judgment and recording values of ninety nine template variables.

(Zeleznikow *et al.*, 1995) stress that leading cases are not suitable for the training of machine learning algorithms to mimic reasoning. Data for the Split Up project was gathered from cases decided between 1992 and 1994. The cases examined had been decided by one of eight different judges. Contradictions in data were expected in this discretionary domain because different judges may agree on the facts, on the relevant principles and rules and yet still legitimately arrive at a different outcome. Therefore, by training neural networks on data from a number of judges we, in effect, encourage the network to mimic a composite of all judges.

All neural networks were feed forward networks trained with back propagation of errors. This type of network was chosen because it has been used widely and successfully in a number of research and commercial applications.[5] Measures of network performance typically used for neural network training include the number of correctly classified examples and the error rate on unseen training examples. Both these measures proved to be inadequate for this domain because of the presence of contradictory inputs. A simple example illustrates this. We can imagine two cases A and B which have identical inputs yet case A resulted in a 30% determination and case B (made be a different judge) resulted in a 40% determination. The neural network once trained and exposed to the same inputs,

[5] Software used for neural network training was NeuDL (Neural Network Description Language), a description language for the design, training and operation of neural networks developed by Samuel Joe Rogers at the University of Alabama. Neural networks were trained on mainframe computers running Unix for speed and efficiency. However, the Split Up prototype was written using KnowledgePro, an object oriented high level language with a built in inference engine and hypermedia development tools released by Knowledge Garden Inc

outputs a value between the two contradictory values it has seen, 35%. This result is quite acceptable to us, yet, both case A and case B are reported as incorrectly classified by the simple metric of counting correctly classified examples. Purpose built functions were written to measure the output of the network that were more sophisticated than a count of the number of correctly classified training examples. Full details that relate to neural network training including cross validation results and network topologies for each network are beyond the scope of this paper.

4 Split up evaluation

Nine specialist family law solicitors were asked to analyse three cases. The three cases were devised to test diverse marriage scenarios. Given the difficulty in assembling large numbers of specialist lawyers we cannot attempt tests of significance on these results. Table 1 illustrates the percentage of the assets awarded to the husband by the Split Up system and by each of ten lawyers.

	Case A	Case B	Case C
Split Up	55%	50%	40%
Lawyer 1	55-60%	50%	35%
Lawyer 2	55%	50%	35-40%
Lawyer 3	50-55%	50%	40%
Lawyer 4	45%	50%	50%
Lawyer 5	45-50%	50%	40%
Lawyer 6	40%	50%	35%
Lawyer 7	45-50%	50%	35%
Lawyer 9	50%	50%	40%

Table 1: Split Up prediction compared with Lawyers prediction

Cases C and B indicate that Split Up predictions are in line with lawyer's predictions. Furthermore, reasons for their prediction given by Split Up were similar to reasons given by lawyers. Case A was more controversial. This case involved a marriage where domestic duties were performed by paid staff and not by either party to the marriage. Split Up and four of the lawyers interpreted this situation as one where both parties had contributed to the home in equal measure. The remaining lawyers regarded this as incorrect and assigned the majority of the home-maker role to the spouse who had not engaged in paid employment.

5 Conclusion

We have demonstrated our belief that reasoning in discretionary domains is indicative of a type of open texture often overlooked by AI and Law researchers. This type of open texture needs to be tackled in a different way to the methods used for classification anomalies, defeasible rules or vague terms. We have illustrated the benefits of an integration of the connectionist paradigm with rule based reasoning for reasoning in the discretionary domain of family law in Australia. Our approach generates explanations for conclusions reached quite independently of inferencing methods used to reach those conclusions. Assumptions underlying this draw jurisprudential support from the movement known as legal realism. The foundation our approach is a knowledge representation schema based on the structure of arguments proposed by Toulmin.

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