Split Up: The use of an argument based knowledge representation to meet expectations of different users for discretionary decision making

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Abstract

Split Up is a rule / neural hybrid that represents knowledge using frames based on the argument structure proposed by the British philosopher, Toulmin. Split Up makes predictions about marital property following a divorce in Australia; a domain that is considered discretionary in that a judge has considerable flexibility. The end users of Split Up are judges and registrars of the Family Court of Australia, mediators and lawyers. Each end user has specific and divergent needs and thus uses the system in different ways however all users rely on effective explanations. The argument based representation of knowledge enables the system to have the flexibility required of different users, to generate effective explanations and also facilitates knowledge acquisition. The framework has been used to integrate rules with neural networks but can easily be used to integrate other inferencing methods.

1. Introduction

Discretionary fields of law are those in which a decision maker has a considerable degree of flexibility in determining an outcome. Family law in Australia is considered discretionary because a judge of the Family Court of Australia, in allocating property to couples following a divorce is required by statute to take various factors into account but has discretion in allocating a relative weighting to each factor. For example, the principle statute mandates that the health and age of both parties are relevant considerations yet is silent on their relative importance.

Modelling discretionary reasoning is difficult. Attempts to do so using heuristic rules has been found to be limited by (Edmunds and Huntley 1992) and also by (Stranieri and Zeleznikow 1992). The application of neural networks to modelling discretionary reasoning is suitable if sufficient past decisions can be collected from Courts to form a training set. Once trained, the network, exposed to a new case will output a result consistent with patterns of decisions in previous cases. However, neural networks have not often been used to model legal reasoning principally because explanations for neural network inferences are difficult to generate and because sufficiently large numbers of past cases often do not exist.

Split Up is a rule - neural hybrid system that integrates twenty neural networks with fifteen rules sets. The system predicts the percentage of marital property a Family Court of Australia judge will award litigants to a divorce. Consultations with domain experts from a state funded legal service identified a total of 94 relevant variables. Data reflecting values for these variables has been collected from over one hundred judgments made by decision makers in the Family Court. The data was used to train neural networks.

The system is currently being used by registrars (judicial assistants) and judges of the Family Court, mediators from a counselling service and four legal firms. The needs of each group of user is quite distinct and as a consequence the way the system is used and ensuing benefits differ. For example, registrars of the Family Court are required to attempt to mediate a settlement before a dispute is tried by a judge. This involves informing litigants about the basics of family law and judicial heuristics. Lawyers are less interested in educating their client but need to organise their arguments, validate their own predictions and be reminded of cases and statutes that would strengthen (or weaken) their arguments. Judges are required to arrive at an equitable outcome in the shortest amount of time possible.

The knowledge representation central to Split Up is a structure based on the argument structure proposed by (Toulmin 1958). The argument based framework used in Split Up is not limited to rules and neural networks but can easily accommodate other forms of inferencing including fuzzy logic, inferential statistics and non-monotonic logic. The argument based structure we use has the following benefits:

- Explanations are generated independently from the reasoning method used to infer an outcome. Explanations are not traces of the inferencing and can be generated whether a neural network or a rule set produced the outcome.

- Knowledge acquisition from expert interview is facilitated because the argument structure enables domain experts to decompose the task of predicting a percentage split of marital assets into smaller sub-tasks. Each sub task can be modelled with a relatively small neural network that requires far fewer past cases to train than is the case for a large network.

2. The argument based frame in Split Up

(Toulmin 1958) suggested that reasoning that humans display in practice was distinct from the syllogistic reasoning that preoccupies logicians. Reasoning, in practice can be seen to conform to a simple structure now called a Toulmin argument structure (TAS). According to Toulmin an argument, regardless of the domain, makes a **claim** from **data**. The **claim** or assertion is made with a force called the **modality**. A **warrant** explains why the assertion follows from the datum and a **backing** provides evidential support for the validity of the warrant.

According to (Toulmin 1958), the warrant component of an argument is not the same as the universal premise (or rule) of syllogistic reasoning. Split Up presents a variation to the standard Toulmin Argument Structure in that a warrant represents a reason for why a data item is relevant to the argument. Furthermore, the Split Up structure differs from the Toulmin structure in its inclusion of an inference procedure used to infer a claim value from data variable values. In Split Up the inference procedure is a rule set for 15 arguments and a neural network for 20 others. Figure 1 represents the variant on the Toulmin structure used in the Split Up system.

Figure 1 illustrates three data items are directly relevant in determining a value on the claim variable. The inference procedure that is used to infer a claim value from data is a neural network. The reason that the data item "The husband has contributed more to the marriage" is relevant in the *percentage split* argument within Split Up is that a Statute makes this relevant. Section 79(4) of the Family Law Act obliges a decision maker to take past contributions into account. The reason the data item 'The marriage is of Z wealth' is relevant is that a precedent case has made it relevant. These reasons constitute a type of warrant we call the Relevance warrant. Figure 1 illustrates an additional type of warrant called the Inference warrant. This type of warrant represents reasons for why the inference procedure nominated is appropriate.

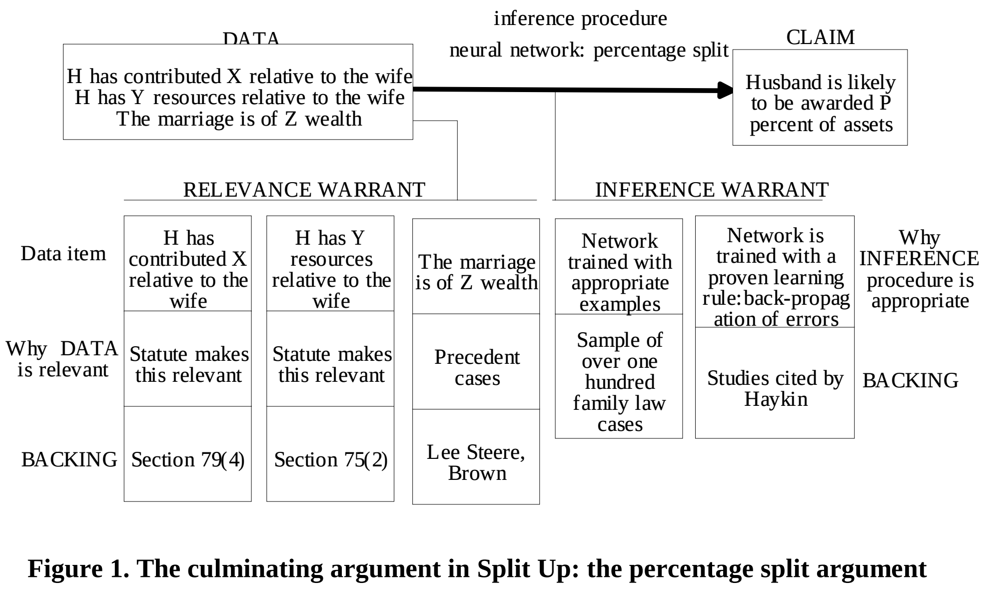

Figure 1. The culminating argument in Split Up: the percentage split argument

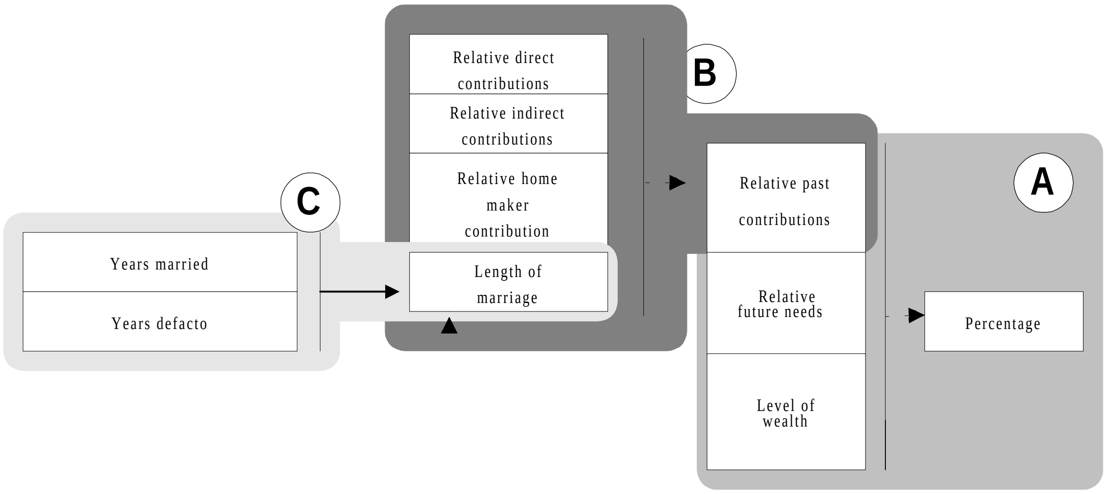

Figure 2. Data and Claim components of three arguments in Split Up

A chain (or tree) or reasoning emerges with the use of TAS because the claim of one argument is used as the data item of another as illustrated in Figure 2. This diagram represents only the data and claim components of three arguments. The data item *H has contributed X to the marriage* in Figure 1 is labelled the relative past contributions in Figure 2. This is the assertion of another argument (B) which has four data items. Knowledge is represented as a tree of arguments.

A central feature of the structure of each argument in Split Up is that the relevance warrant and the inference warrant in Split Up do not contribute to the generation of an outcome. A claim is inferred using the data items and inference procedure components. A claim is explained using the data and warrant components. The procedure used to generate an outcome is separated from the components used to explain the outcome.

The separation of reasoning and explanation advanced in Split Up relies very heavily on the concept of relevance. We adopt a pragmatic approach to the definition of relevance because a formal definition for relevance remains elusive. (van Dijk 1989) maintained that arguments can be made for the grounding of relevance in the pragmatics of natural language. He points out that well formedness is a concept central to syntax, truth or meaningfulness is a concept central to semantics, but the concept central to pragmatics is a appropriateness. Two propositions are relevant if a speaker considers their connection appropriate in a particular pragmatic context. A data item is relevant to an argument if a sentence expressing the reason for the relevance can be uttered and appear comprehensible. The hair colour of the judge was not considered relevant in any Split Up argument because domain experts could think of no reason that would make this feature relevant.

The structure used in Split Up omits the modality and rebuttal component of the original Toulmin structure. This was done for simplicity though future research is planned to develop the framework into a dialectical model that includes the rebuttal and modality.

The use of argumentation to represent knowledge and to model reasoning is a relatively recent phenomena in artificial intelligence. Researchers that use the original TAS as a knowledge representation framework include (Dick 1987), (Marshall 1989), (Bench-Capon, Lowes and McEnery 1991), (Clark 1991), (Johnson, Zualkernan and Tukey 1993) and (Ball 1994). Argumentation has also been used as the basis of a dialectical model with a non-monotonic logic by (Gordon 1993), (Farley and Freeman 1995), (Dung 1995) and with case based reasoning by (Ashley 1991).

3. Making and explaining inferences

Split Up is being used by judges, registrars, mediators and lawyers. Mediators in family law input a party's facts, peruse the resultant prediction and then explore the hierarchy of relevant data, warrant and backing factors with the party in order to inform and educate them. The facts of the other party are then input. Points of divergence between the two parties become obvious and the scale and loci of compromise are more easily identified. Split Up is currently being integrated into a general negotiation support system reported by (Bellucci and Zeleznikow 1997).

The Split Up system used data from commonplace and not landmark cases for neural network training. According to (Zeleznikow, Hunter and Stranieri 1997), commonplace cases are those which are not appealed and set no new or interesting precedent. Landmark cases are not useful for training networks because these cases change the way subsequent commonplace cases are decided.

Jurisprudential purists may object to the distinction between commonplace and landmark cases because a case that seems perfectly today may be used in the future to fundamentally alter a legal principal and thus be a landmark case. However, in practice the distinction between commonplace and landmark cases is used on a daily basis at least by the Family Court in order to decide which cases are to be published by Court reporting services. Over 95% of Australia's 48,000 annual divorces not considered interesting by the Family Court and are therefore not published.

The Split Up user is required to be sufficiently well versed with family law in order to identify a case as one which may potentially be significantly out of the ordinary and thus liable to incorrect predictions by Split Up. Thus the system is not recommended for use by users completely unfamiliar with family law.

Each group of users have a need different information is available to different users. This is accomplished in Split Up by placing the user in control of the explanation generation. The explanation facility is effective because it is tied closely to the argument frame but has limitations because it cannot engage the user in a dialogue.

The ability to explain reasoning is important for most tasks humans engage in. Explanations for predictions made by Split Up are under the guidance of the user. On presentation of a percentage output (or the claim of any argument) the user is presented with the data items that led to the prediction. She may:

- question the relevance of the data items in which case the relevance warrant and backing are retrieved from the argument frame. The warrant and backing elements often refer to precedent cases, or sections of a relevant statute. These references are implemented in Split Up as hypertext links to the full text.

- question the way in which the claim was inferred from the data in which case the inference procedure, warrant and backing are presented.

- question the data item value in which case the argument that produced that item as a claim is retrieved and the explanation proceeds with that argument.

Over fifty judges, lawyers, mediators and divorcees that have trialed Split Up report favourable comments regarding the predictions made and the explanations provided by the system. Furthermore, a comparison of Split Up outputs with a panel of eight family law specialists on the same cases demonstrated that Split Up predictions fell within the range of human prediction.

(Bench-Capon, Lowes and McEnery 1991) augment their logic programs with a Toulmin representation and report favourable user response from explanations generated in this way. The generation of an explanation directly from a TAS representation is an example of a types of explanatory system that (Moore 1995) labels the canned text approach. She notes the limitation of a canned text approach to explanation and advocates the generation of an explanatory dialogue that adapts to suit the needs and abilities of different users. We believe that the TAS representation will facilitate the generation of explanatory dialogue and aim to test this in future work. However, a critical component of any work with explanations involves their evaluation.

User satisfaction remains the most appealing criteria to assess an explanatory system. Current research aims to survey three groups of users; judges, registrars and mediators. The criteria for user satisfaction determination derive from (Buchanan *et al* 1995) and are information exchange, useability and attitude.

Another criteria for the evaluation of explanations involves a direct comparison of Split Up explanations with explanations offered in a judgement. This criteria is less appealing than user satisfaction because the explanatory content of judgements vary enormously. We believe this is largely because the explanation in a judgement is a monologue and confirms Moore's insistence on explanatory dialogues.

4. Knowledge acquisition

The argument based framework used in Split Up facilitated knowledge acquisition from experts. Domain experts are asked for factors most directly relevant to the claim in question; at the outset, to a percentage split judgement. The factor(s) elicited as relevant are entered as data components of the argument. The experts are then prompted for their reasons for the relevance of the factors and supporting evidence to justify their reasons. The inference procedure is not discussed during initial expert interviews. When an argument is complete with datum and relevance warrants, the knowledge engineer constructs new arguments for each of the datum components. Each new argument has, as claim, a data item of the completed argument.

In this way, complex knowledge is easily decomposed into conveniently sized frames. The expert is not necessarily burdened with the need to identify inference procedures at the same time as identifying relevant concepts. After the relevant factors for a claim are elicited, the knowledge engineer decides whether the manner in which factors combine are most plausibly captured by expert heuristics, or with a neural network trained with past data, a fuzzy rule, inferential statistics method or some other method.

As indicated above, 20 arguments were regarded as more suitable for a neural network inference method than a rule set. This was done on the basis of a classification scheme based on the extent to which experts believed an argument's data items combined in a structured way to infer a claim (the open textured dimension) and the extent to which experts believed the argument contained all items that could conceivably be regarded as relevant (we called this the boundedness dinmension in Stranieri *et al* 1998). For example according to experts there is a high liklihood that no additional data items will be found to be relevant for Argument C in Figure 2. Furthermore, experts could identify how the data items combined to yield a claim value. We call Argument C a narrow bounded argument and as such, conclude that a rule set derived from heuristics is adequate. Argument A is far more open textured because the way in which items are combined by judges seemed far more discretionary and opaque. Argument A was classified a Wide bounded argument and as a neural network was used as a consequence. We believe that tasks classified unbounded cannot be modelled using any techniques because experts suspect that data items important for an assertion are unknown at the present time.

The argument structure 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 four template variables.

Each of the 20 networks were relatively small because of the task decomposition that the TAS enabled. We chose therefore to represent each data item as a bit string corresponding to value categories. For example, the claim of Argument C in Figure 2 had values 'very long', 'long', 'about average', 'short' and 'very short'. A long marriage was represented as bit string 01000.

Each network was trained using five fold cross validation on training/test set partitions of varying sizes using backpropagation of errors. We abandoned the number of test examples correctly classified as a performance criteria in order to avoid overfitting the data. Instead, we used a metric that measured the magnitude (but not the direction) of the error. A network output of 00001 erred by size 3 if the actual was output 01000. We ceased training when the average (over cross validation sets) proportion of errors of magnitude 3 (or more) was less than or equal to 3%.

Zeleznikow and Stranieri (1997) describe the process of collecting data to train networks within a TAS framework as one of few examples of knowledge discovery from databases (KDD) in the legal domain. Courts in the future may be enticed to collect data that reflects the reasoning processes used by judges in a computer friendly format so that KDD can be performed easily. Trend analysis can then become an automatic feature of any jurisdiction.

Split Up was written using the knowledgePro object-orientated, hypertext development environment for a PC/Windows platform. This environment was most convenient as each argument is implemented as an object and links within explanations were implemented as hypertext links. Neural networks were trained using public domain Unix based software tools but once trained a look-up table was created with each network. (Lewis, Stranieri and Zeleznikow 1997) describe a simple algorithm for the generation of, and retrieval from a look-up table. The look-up table stored the network output for every possible input and were transferred to the PC environment. This resulted in very fast inferences.

5. Conclusion

The TAS based knowledge representation structure used in Split Up represents a contribution to the conceptual modelling of any domain that is discretionary. Currently, the method used is being used for the integration of information retrieval with reasoning in a domain considerably more discretionary than family law; refugee law.

The Split Up system demonstrates a knowledge representation that facilitates the integration of rule based reasoning with neural networks. The flexibility inherent in this knowledge representation enables the generation of explanations that are useful to user's with different information needs. However, systems such as Split Up have to potential to make a significant impact on the practice of law.

7. References

Ashley, K. D. 1991. *Modelling legal argument: Reasoning with cases and hypotheticals*. Cambridge: MIT Press.

Ball, W.J. 1994. Using Virgil to analyse public policy arguments: a system based on Toulmin's informal logic. *Social Science Computer Review*. Vol: 12 Issue: 1 p. 26-37. Spring

Bellucci, E. and Zeleznikow, J. 1997. Family—Negotiator: an intelligent decision support system for negotiation in Australian Family Law. *Proceedings of the Fourth Conference of the International Society for Decision Support Systems,* Lausanne, International Society for Decision Support Systems:359-373.

Bench-Capon T.J.M, Lowes, D. and McEnery, A. M. 1991. Argument-based explanation of logic programs. Vol 4 No 3. Sept *Knowledge Based Systems* p177-183

Buchanan, B., Moore, J., Forsythe, D., Carenini, G., Ohlsson, S. and Banks, G., 1995. An Intelligent interactive system for delivering individualised information to patients. *Artificial Intelligence in Medicine*. 7 (1995) 117-154.

Clark, P . 1991. *A Model of Argumentation and Its Application in a Cooperative Expert System.* PhD thesis. Turing Institute. Department of Computer Science. University of Strathclyde. Glasgow.

Dick, J. P. 1991. *A conceptual, case-relation representation of text for intelligent retrieval.* Ph.D Thesis. University of Toronto. Canada.

Dung, Phan Minh. 1995. On the acceptability of arguments and its fundamental role in non-monotonic reasoning, logic programming and n-person games *Artificial Intelligence*. v. 7, issue 2., p. 321-357.

Edwards, L. and Huntley, A. J. K. 1992. Creating a Civil Jurisdiction Adviser. Law, *Computers and Artificial Intelligence*: 1(1), 5—40.

Farley, A. M and Freeman, K., 1995. Burden of Proof in Legal Argumentation. Proceedings of *Fifth International Conference on Artificial Intelligence and Law*. May 21-24. Boston. ACM Press, USA. p156-164.

Gordon , T. F. 1993. The Pleadings Game. *Proceedings of Fourth International Conference on Artificial Intelligence and Law*. Oxford. ACM Press. New York. pp10-17.

Johnson, P. E., Zualkernan, I. A. and Tukey, D. 1993. Types of expertise : an invariant of problem solving. *International Journal of Man Machine Studies*, v. 39, pp. 641.

Lewis, B., Stranieri, A and Zeleznikow, J. 1997. Scaling of neural network inferencing by efficient storage and retrieval of outputs *Applied computing 1997 : proceedings of the 1997 ACM Symposium on Applied Computing*. p. 10-14.

Marshall, C. C, 1989. Representing the structure of legal argument. *Proceedings of Second International Conference on Artificial Intelligence and Law.* ACM Press, USA. pp121-127.

Moore, J 1995. *Participating in Explanatory Dialogues. Interpreting and Responding to Questions in Context.* MIT Press. Cambridge MA.

Stranieri, A. and Zeleznikow, J. 1992. SPLIT-UP—Expert system to determine spousal property distribution on litigation in the Family Court of Australia. *Proceedings of Artificial Intelligence Conference (Australia)-92*, Hobart: World Scientific, 51-56.

Stranieri, A., Zeleznikow, J., Gawler, M. and Lewis, B. 1998. A hybrid—neural approach to the automation of legal reasoning in the discretionary domain of family law in Australia. To appear in *Artificial Intelligence and Law*.

Toulmin, S. 1958. *The uses of argument.* Cambridge: Cambridge University Press.

van Dijk, T. A. 1989. *Relevance in logic and grammar*. in *Directions in relevant logic* / J. Norman and R. Sylvan (Eds.). p. 25-57.

Zeleznikow, J. Hunter, D. and Stranieri, A. 1997. Using cases to build intelligent decision support systems. Database Applications Semantics — Proceedings of the IFIP Working Group Stone Mountain, Georgia, USA. May 30 - June 2. 1995. Edited by Meersman, R. and Mark, L. Chapman—Hall, 443—460.

Zeleznikow, J. and Stranieri, A. 1997. Knowledge discovery in the Split-Up project. *Proceedings of Sixth International Conference on Artificial Intelligence and Law*, ACM: 89-97.