Machine Learning and Legal Argument

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Abstract

Although the argumentation justifying decisions in particular cases has always been central to AI and Law, it has recently become a burning issue as black box machine learning approaches become prevalent. In this paper we review the understanding of legal argument that has been developed in AI and Law, and indicate the most appropriate ways in which Machine Learning approaches can contribute to legal argument. We identify some key questions that must be explored to provide acceptable explanations for legal ML systems. This provides the context and directions of our current research project.

Keywords

Machine Learning, Legal reasoning, Justification

1. Introduction

The use of Machine Learning (ML) techniques to produce algorithms to classify new instances on the basis of a large set of past instances has become prevalent: so much so that this approach is now almost synonymous with "Artificial Intelligence" in the popular press. Where these systems explain their reasoning it is typically in terms of the algorithm: they may identify the words of features that contributed most to the classification, or display some sort of visualisation in the form of a "heatmap" [23]. Explanations of legal decisions are, however, somewhat different from those required in many other ML applications. The outcome of a case is not a property waiting to be discovered, but the result of a decision made by the appropriate empowered authority, such as a judge. Now, it may be that the *explanation* of how the decision was made can be something non-legal: for example it has been found that judges can be more lenient before lunch and towards the end of the day [19]. Such an explanation is not, however, what is required for a legal decision. What is required is a *justification* of how the decision represents the application of the law. The explanation of legal decisions must take the form of an argument able to persuade its audience of the correctness of the decision, in terms of the applicable law. To achieve this, the argument must be couched in natural terms, so that the decision can be seen to follow from the law, rather than in the quasi-statistical terms that would explain how an ML algorithm had arrived at its prediction.

There has in recent years been an explosion of interest in the application of ML techniques to law. Several tasks have been addressed including case retrieval [33], summarisation [14],

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and legal argumentation mining [39]. In this paper, however, we will focus on the important class of applications intended to support the task of deciding legal cases. This task has received attention from many researchers: the European Convention on Human Rights (ECHR) alone has been the subject domain of a number of studies including [4], [26], [18], and [24].

A prediction of the outcome of a case on its own, however, offers little help to a person charged with deciding the case. This is discussed in [12] where it is cogently argued that, without an explanation of why the case was so classified, the adjudicator has no reason to follow the advice. The performance of prediction systems is by no means perfect (typically less that 80%), so there can be no assurance that the outcome will be correct, and the law requires a very high degree of certainty. Judges will therefore still need to form their own independent opinion and without the reasons for the machine opinion they would have no reason to give any weight to that of the machine. Moreover, there are reasons to believe that the machine will not be able to learn the applicable law. For one thing, as argued in [8], the data used to train the system is likely to contain decisions reflecting bias and misunderstanding, and changes in law and societal values mean that decisions become increasingly unreliable as they age [26]. Moreover, even if the dataset is perfect, empirical work has shown that it may fail to find the correct rationale for its decisions (see [6] and [35]). This means that an explanation of the machine's suggestion is required if incorrect rationales are not to be applied.

We will consider how ML can support legal decision making, given that what is required is an outcome accompanied by an argument which justifies that outcome in terms of the applicable law. We will first review work on the generation of such arguments in AI and Law, then consider what part ML approaches might play and how we are addressing this topic in our current project.

2. Modelling Legal Argument in AI and Law

Arguments justifying legal decisions have been a central concern of AI and Law since 1976 when McCarty's TAXMAN [25] attempted to model both the majority and minority arguments in the famous tax law case of *Eisner v Macomber*. Most influential has been the stream of work on modelling US Trade Secrets Law originating in HYPO [31], developed further in CATO [5] and subsequently explored by many others [7]. This work has shown that legal argumentation in cases can be seen as passing through a series of layers, as articulated in [2].

The top layers supply a logical framework: this may derive from statute law [34], or emerge from case law [30]. Thus for Trade Secrets Law, in order to find for the plaintiff, the information must be both a Trade Secret and have been misappropriated. To be a Trade Secret the information must be valuable and have had adequate measures taken to protect its secrecy. To have been misappropriated there must have been a breach of confidence or the use of improper means to obtain the information. These elements, known as *issues*, form an and/or tree with the children providing necessary and sufficient conditions for their parent. At this level the explanation can be in terms of these logical rules: e.g. *find for the defendant because the information was not a Trade Secret* and *it was not a Trade Secret because the measures taken to protect its secrecy were inadequate*.

The next layer comprises *factors*, a notion made popular by CATO [5]. Factors are stereotypical patterns of fact that provide a (non-conclusive) reason to decide for one side or the other. In

Trade Secrets Law, these include: whether the information was *disclosed in negotiations*; whether the information was *known to be confidential*; and the ease with which the information was *reverse engineerable* by inspecting the product. Like issues, factors can form a tree, with abstract factors explained in terms of base level factors. Unlike issues, factors do not provide necessary and sufficient conditions for their parents: they provide reasons for and against the presence of the parent, which must be weighed against one another and a preference expressed. Precedent cases provide a source of such preferences. Where the question has been considered previously, the decision in the previous case constrains the decision: where the question has not previously arisen the court must make a choice which will constrain future decisions. Thus, at this layer we get a rather different style of argument, taking the form of a statement of the factors (the reasons for both sides), the status of the issue under consideration, and a precedent justifying the preference that gave that status. For example *where the information had been disclosed in negotiations but the defendant was aware that the information was confidential, a duty of confidence existed (cite National Rejectors v Trieman 1966).*

Below factors are the *facts*, and it is on the basis of these that the factors are ascribed. Often this will require argument: for example if the defendant has claimed that the information was not valuable because it could be reverse engineered, the court will need to look closely at the "ease or difficulty with which the information could be properly acquired or duplicated by others" to decide whether the facts do indeed suggest that this was a reason for the defendant and that the factor *reverse engineerable* can be ascribed. An example of an argument at this level can be found in *Technicon Data Systems Corp. v. Curtis 1000, Inc*: "The Court reasoned that the process had required over two-thousand hours, and still had not yielded a fully functional product. The Court held that this amount of time indicated that a trade secret was not readily ascertainable."

At the very lowest layer is the evidence on which the facts are based, which will include witness testimony, forensic evidence and the like. The reasoning here is not specifically legal, but is similar to that used to establish the truth of matters in everyday life. Indeed, the facts are often decided not by lawyers, but by a lay jury. In higher courts, where a decision is appealed, the facts are usually taken as those established by the lower court. Although arguments based on evidence have received attention in AI and Law in, for example, [13] and [37], we will not consider them further in this paper, concentrating instead on the distinctively legal arguments.

2.1. Layers of Reasoning in AI and Law

Although the complete justification of a legal decision would involve starting from the evidence and working through the facts, factors, and issues to reach the final verdict, few approaches have examined the entire process. The focus in evidential approaches such as [11] was resolving conflicting stories as to the facts, and other systems have covered different parts of the range.

Approaches based of the formalisation of legislation [32] are concerned only with the uppermost levels: they ask users to resolve the issues and the system provides the outcome based on their answers. CATO [5] took the factors as input and produced arguments for both sides, leaving it to the user to resolve these arguments to reach a decision. IBP [17], extended the CATO approach with a logical model of the issues so that it could predict outcomes. HYPO represented cases as facts and identified the applicable dimensions to enable factors to be

Table 1
Layers of Statements in a Legal Decision and Some Example Systems

Statement Type	BNA [32]	HYPO [31]	CATO [5]	IBP [17]	Bex *et al.* [11]	NIHL [3]
Outcome	X			X		X
Issues	X		X	X		X
Factors		X	X	X		X
Facts		X			X	X
Evidence					X	

ascribed. It did not use issues and the user was left to decide which side was favoured on these dimensions, and how these resolved the overall case.

The ANGELIC methodology [1] addresses all the layers above evidence. Using ANGELIC, knowledge is represented as an Abstract Dialectical Framework (ADF) [16]. The ADF has the form of a tree, beginning with verdict and then working through the different statement types. In an ADF each node is associated with acceptance conditions local to the node, which determine the status of the node in terms of its children. Because these acceptance conditions are local to a node they can reflect the different reasoning styles used for the different statement types: the upper layers can use propositional formulae, while the issues can be resolved using prioritised combinations of factors to reflect reasoning with the weighing of reasons for and against, often termed 'balance of factors' reasoning [36]. At the very lowest level the use of thresholds can convert dimensional facts and probabilities into factors. A full application of the methodology to a real world application is given in [3]. An example ADF for Trade Secrets law is given in [9]. The coverage of various systems is summarised in Table 1.

3. Explaining Predictions from ML Approaches

Little attention is paid to the explanation or justification of the prediction in current work using ML, e.g. [4], [26], [18], and [24]. One of them [4], however, did offer a list of twenty words, listed in order of their Support Vector Machine weight. The list for violation of article 6 in the ECHR domain, was:

> court, applicant, article, judgment, case, law, proceeding, application, government, convention, time, article convention, January, human, lodged, domestic, February, September, relevant, represented

Such a list inspires no confidence in the sound legal basis of the prediction: indeed finding month names among the most predictive words suggests rather that the algorithm is relying on features of the data which have no legal significance and so should be irrelevant. Certainly there is nothing here that would form the basis of a persuasive argument. A subsequent work [18] did not attempt to provide any justification and commented on those produced in [4] saying that they "are far from being justifications that legal practitioners could trust".

The above systems take as input a natural language description of the facts of the case and output a prediction of the outcome. But, as we discussed in the previous section, legal reasoning must pass through several stages between facts and outcome, and arguments justifying the outcome are naturally expressed in terms of issues and factors, not facts. The justification needs to bridge this conceptual gulf between outcome and facts by the use of legally pertinent legal concepts: issues and factors. This suggests that if we are to be able to justify the outcome, we need to learn the factors present in the case.

This is the basis of the approach taken by Branting *et al.* [15]. Their approach is applied to World Intellectual Property Organization (WIPO) domain name dispute cases and exploits structural and semantic regularities in case corpora to identify textual patterns that have both predictable relationships to case decisions and explanatory value: these regularities essentially correspond to factors. The approach used is a semi-supervised one that makes use of a manually annotated set of representative cases. The manually annotated set is a very small proportion of the available corpus (25 of the 16,024 available).

Branting *et al.* in [15] do not propose any particular method of explanation using the factors, One possible model, used in [28], is provided by CATO. In CATO the justification takes the form of a three-ply argument. In the first ply a proponent cites the most-on-point precedent (i.e. the precedent with the greatest overlap of factors, irrespective of which side they favour, decided for the side being argued for). In the second ply the opponent either cites a counterexample (a case which favours the other side and is at least as on point as the case cited by the proponent) or distinguishes the precedent by pointing to a pro factor in the precedent but not the new case, or a con factor in the current case but not the precedent. In the third ply the proponent offers a rebuttal by distinguishing the counterexamples, or downplaying the distinguishing factor by pointing to a factor which can cancel the additional factor or a factor which can be substituted for the absent factor. These moves were represented as a set of argument schemes in [29], and [28] builds a 3-layer tree based on these schemes. In CATO, the user must decide whether the rebuttals succeed or not but, if we have a predicted outcome, we can explain it by making that side the proponent and knowing that the rebuttal of the opponent's objection will have succeeded in order to establish that particular decision.

This technique is illustrated in [28] with an example of three cases based on US Trade Secrets Law. The cases, which we have given mnemonic names, are shown in Table 2:

Table 2
Cases in the Example From [28]

Case	Outcome	Plaintiff Factors	Defendant Factors
Deceived	P	SecurityMeasures Deception	Disclosures AvailableElsewhere
NoMeasures	D	Bribery	Disclosures AvailableElsewhere
Bribed	TBA	Bribery SecurityMeasures	Disclosures ReverseEngineerable

If the new case, *Bribed*, is decided for the plaintiff we can form a tree of arguments as shown in Figure 1.

Because the decision was for the plaintiff, we know that the distinctions were successfully substituted or cancelled, but in fact not all of the arguments should succeed. Examining the nodes with the benefit of domain knowledge, we can see that *Bribery* can substitute for *Deception*, because they are different forms of improper behaviour. *Deception* cannot, however, cancel *AvailableElsewhere* because they relate to two quite different issues. Similarly while *AvailableElsewhere* can substitute for *ReverseEngineerable*, *Bribery* cannot be substituted for it

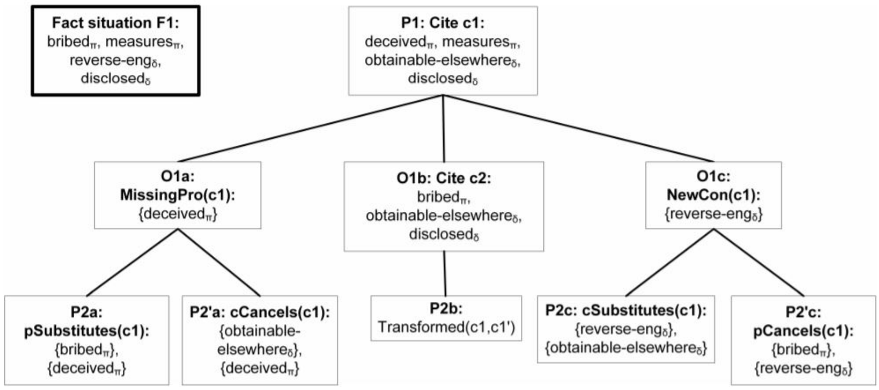

Figure 1: Example Dialogue Tree From [28]

because it relates to a different issue. The problem is that a 'balance of factors' argument is being used to explain the case as a whole, whereas this form of argument is only appropriate to the layer in which issues are resolved. The need to use factors to justify the resolution of issues, and then issues to justify the overall decision is argued in [10].

Thus in order to provide a good justification, it is necessary to have a knowledge of the domain structure in terms of issues and factors, so that the appropriate style of argumentation can be used at each level. This structure is provided in [15] because the initial annotations identify argument elements including issues and factors. The required analysis is also encapsulated in the ADF produced by the ANGELIC methodology [1].

There remains the task of justifying the attribution of the factors on the basis of the facts. This stage of the argument has received little attention in the AI and Law literature, which has typically taken the factors present in a case as given. The experiments in [15] suggest that highlighting the predictive elements in the natural language statement of the facts description did not provide a useful justification of the overall decision. It may, however, be that identifying the elements in the fact description used to ascribe the factors, does provide a helpful justification of this step. This is an idea worth exploring.

4. Roles for Machine Learning

Justification of a legal decision needs two components. First, an understanding of the legal domain, as established in statute and case law, is needed to structure the justification and to enable a smooth passage from facts to factors to issues to the overall outcome. Second, knowledge of the individual case is needed so that it can be related to this structure. Structural knowledge comprises:

- The issues that must be resolved if a decision is to be made for a particular party, and the logical relations between them;
- The factors that are used to resolve the issues, and the preferences between them established by precedent cases;

- The facts which need to be considered to ascribe the factors. Again this may require the use of precedents to establish such things as thresholds such as how readily the information must be ascertainable to allow the ascription of say, the *ReverseEngineerable* factor.

All these elements are identified by manual analysis in traditional approaches to AI and Law as represented by [5] and [1] and are also needed in the semi-supervised approach of [17]. But the question arises as to whether these elements can be identified by ML. There is some prospect that they can. The inductive logic programming approach of [27] was able to derive an effective set of rules from a set of facts. These rules were able to distinguish the relevant facts from the irrelevant facts and the antecedents grouped together facts which were related to a given issue. In the domain used by [27], the facts provided necessary and sufficient conditions for the outcome, and so the antecedents of these rules resembled issues. This is because the example domain contained no 'balance of factors' style reasoning. One might speculate that in a less precisely defined domain, the antecedents would identify factors rather than issues. In such a domain the use of association rule mining as in [38] might be more effective, given that the factor-based rules would be defeasible and provide varying degrees of support.

Thus with regard to the structural knowledge of the domain, the question is whether machine learning can identify the elements required to build a justification: issues and factors. With regard to individual cases, prediction of an outcome is not enough: a justification, couched in legal terms, is required, whether to support a judge making the decision, or to present the reasoning to the public in an acceptable way, given the right to explanation in law [22]. Therefore as well as predicting the outcome, the machine learning system should assign factors to particular cases, as recommended by [15]. Given the factors, a justification of the outcome can be produced, using techniques such as those suggested in [28], perhaps modified to take account of issues as suggested in [10].

5. Concluding Remarks

We have reviewed how legal decisions have been explained in AI and Law, and the part ML might play. We are currently engaged in a project, motivated by the above considerations, exploring how ML techniques can be applied to support making and justifying legal decisions. We will attempt to answer a number of research questions. We will address the domain of the European Convention on Human Rights, since there are a number of existing ML approaches for comparison and inspiration, and also the use of more traditional techniques produced an ADF for Article 6 [20] and a very detailed ADF for deciding questions of admissibility of applications [21]. We will begin by attempting to identify factors to construct an explanation using the pre-existing ADF of [20]. Next we will attempt to extend the explanation beyond what is found in CATO inspired approaches, such as [28], to offer an explanation of why the particular factors were ascribed to the case in terms of the case facts. If we are successful in these two objectives, we will then explore the possibility of learning the domain structure.

Explorations will in turn raise a number of questions, both with regard to ascription in individual cases and to understanding the domain structure, including:

- To what extent is the ML process scalable in terms of cost in time and space resources?

- How close in terms of fidelity are elements identified by ML to those produced by traditional analysis methods?
- The domain will evolve over time: how can changes in social preferences and the identification of new factors to consider be accommodated?

We will also wish to perform evaluation with users to explore questions of how the explanations are received by different audiences, such as:

- To what extent do relevant audiences trust different explanation techniques?
- How well do relevant users perform their different tasks when interpreting and applying the explanations to new instances?

The development of an effective ML system will be underpinned by three core aspects: training on a small annotated data set; leveraging domain knowledge as prior constraints for the learning; and reinforcement learning to allow for more focused application of expert annotation. We will examine the interplay between these three aspects, with the assistance of legal expertise, with the intention of crafting an ML system that can ascribe factors with suitable fidelity and justification. If successful, we then expect to apply the same three core aspects to the larger problem of learning the domain structure, in order to produce high fidelity and justifiable case outcomes directly from the facts of the case.

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