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Predicting Outcomes of Case-based Legal Arguments

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ABSTRACT

In this paper, we introduce IBP, an algorithm that combines reasoning with an abstract domain model and case-based reasoning techniques to predict the outcome of case-based legal arguments. Unlike the predictions generated by statistical or machine-learning techniques, IBP's predictions are accompanied by explanations.

We describe an empirical evaluation of IBP, in which we compare our algorithm to prediction based on Hypo's and CATO's relevance criteria, and to a number of widely used machine learning algorithms. IBP reaches higher accuracy than all competitors, and hypothesis testing shows that the observed differences are statistically significant. An ablation study indicates that both sources of knowledge in IBP contribute to the accuracy of its predictions.

1. PREDICTING CASE OUTCOMES

Most AI and Law models of case-based legal reasoning have eschewed predicting the results of new cases in favor of making arguments, e.g., HYPO (Ashley 1990), CATO (Aleven 1997), GREBE (Branting 1999), CABARET (Rissland & Skalak 1989); but see (Aleven 2003) and (Popple 1993). Early projects (McKaay & Robillard 1974) used logistic regression or basic nearest-neighbor methods for prediction, but did not employ legal reasoning techniques.

The focus of legal reasoning research on argumentation is understandable. The goals of automatically generating arguments about a new case and predicting its outcome coexist in uneasy, although potentially productive, tension. Legal argumentation is fundamentally normative. The goal of case-based AI models of legal reasoning is to generate reasonable precedential arguments and counterarguments, regardless of empirical likelihood. Even when an advocate cites a past similar case as an authority, the assumptions are that the court "got it right" in the precedent and that the advocate can show how the normative reasoning maps onto the new case (Hafner & Berman 2002; Ashley 2002) or even determines its outcome (Bench-Capon & Sartor 2001; Horty 1999). The point of an advocate's distinguishing the cited case is to show factual differences that warrant a different normative result (Ashley 2002). An advocate can also argue that the prior court was wrong, raising the interesting question of the precedent's continuing effect under the doctrine of *stare decisis* (Alexander 1989).

Predicting the outcome of new legal cases, on the other hand, is fundamentally historical and empirical. Courts may have decided many more or less similar cases. Given a database of classified cases represented in terms of features that strengthen or weaken the classification, one can apply statistical or symbolic machine learning techniques to induce general rules for classifying new cases and predicting their outcomes. Even if these generalizations are rules, however, they are not normative rules but empirical rules about normative decisions.

1.1 Problems with Empirical Generalization from Cases

Prediction has not been studied to the extent argumentation has in recent AI and Law research. Empirical methods for legal prediction pose a number of potential problems, and it remains an open question what limits constrain prediction as applied in practice.

The classical approach for predicting outcomes employs statistical or inductive models to generalize past cases. This prediction may be "right" from an empirical viewpoint, and yet be dead wrong from a normative one. A novel factual circumstance in the new case may require a different outcome than the one predicted. General social, economic, or technological changes may call into question whole lines of precedents. Statistical generalizations, moreover, often have exceptions. A prediction based on an empirical generalization of past cases may miss an analogy to an apparently anomalous precedent or counter-instance whose application may, nevertheless, be supported by a convincing normative argument.

Prediction presents various other problems, as well. Statistical prediction of case outcomes or feature weights must deal with the problem of small or biased samples. Even in enormous on-line full-text legal databases, only litigated cases involving hard choices among evenly balanced conflicting strengths and weaknesses may be reported; many cases get settled and are not available for inclusion in the sample. It is an important question whether predictions based on such a biased sample will, for instance, be useful for legal practitioners.

Furthermore, algorithms that rely solely on assigning quantitative feature weights are problematic in so far as they are not sensitive to a problem's particular context (Ashley & Rissland 1988) or do not support reasonable legal explanations of why the predicted winner should win (a problem, for instance, with (McKaay & Robillard 1974; Popple 1993)).

Finally, statistical algorithms require sufficiently large data sets, and as a rule of thumb, the harder the task, the more cases are needed. This adds an extra problem for predicting the outcome of legal cases. The cases are texts and the features must be represented in an appropriate form for machine learning. So far, however, representation is a manual process (but see (Brüninghaus & Ashley 2001; Daniels & Rissland 1997)).

1.2 Integrating Argumentation and Prediction

Nevertheless, AI models of legal reasoning can play a role in predictive generalizations, when the system has a database of cases, represented by numerous factual and conceptual features that figure in their results (e.g., stereotypical facts, legal arguments, or legal conceptual analysis).

Most of these representations and case bases can be made the basis of empirical predictions using general statistical techniques, machine learning algorithms, including, e.g., neural networks (Zeleznikow & Stranieri 1995), CBR methods, or specially designed algorithms that take some legal knowledge into account. The predictions are subject, of course, to the biases of the systems' usually small and possibly unrepresentative samplings, but they can be generated and they do provide some information that may be relevant, even to the arguments the system generates.

The questions arise therefore: How can, how should the argumentation and prediction tasks interact? Ideally, a creative tension between argumentation and prediction may result from combining normative and predictive knowledge in useful ways. For instance, analyzing induced empirical rules from a normative viewpoint can reveal whether the practical determinants of a result have little to do with what the normative rules say (Eisenberg & Henderson, Jr. 1992). Conversely, analyzing the normative rules from an empirical viewpoint reveals whether they yield the right result as often as lawmakers hope.

Explanations often combine normative and predictive information. One cannot satisfactorily explain an empirical legal generalization by simply listing the positive and negative instances. Rather, one needs to recount normative arguments that could reasonably justify and explain the generalization and its predicted result (Again, the normative counterarguments would be of interest.) Conversely, empirical prediction can supplement the explanation of a normative argument. An empirical prediction that a legal argument, though normatively justified, has little chance of success may help one decide whether to "pick" a legal argument or not, or whether to settle and for how much (Waterman & Peterson 1981). Finally, combining predictive and normative knowledge can be especially productive in improving predictive success.

This paper describes a system that combines normative and predictive information in a novel way. It does not use statistics to generalize from a collection of cases. Instead it combines a model of abstract legal issues and their logical relations with a case-based reasoning component. Because the model of the issues is central to the algorithm, it is named Issue-Based Prediction (IBP). IBP identifies the issues raised in a case and uses a kind of scientific evidential reasoning with cases to resolve conflicting evidence when the issue-related Factors favor both sides. The program not only outputs a prediction, it also provides an explanation in an argument-like outline of its reasoning. In an experiment, IBP's performance was better than several standard machine learning algorithms. We also found in an ablation study that IBP achieves more accurate predictions combining its model of issues and case-based reasoner, than either knowledge source alone.

The rest of this paper is organized as follows. In Section 2, we discuss the knowledge used for prediction in IBP. In Section 3, we introduce the algorithm and illustrate it with an example. In Section 4, we describe some more details of the algorithm. In Section 5, we compare IBP's methods to the argument theory of CATO and HYPO, and discuss an experiment in which these theories were for prediction. In Section 6, we present the results of an experiment in which we compared our implementation of IBP to a number of standard machine learning algorithms. We also discuss an ablation study, in which we explored the role of IBP's knowledge sources, and reasons why some cases are hard to predict. Finally, in Section 7, we conclude after a brief summary of the paper.

2. KNOWLEDGE SOURCES IN IBP

IBP was developed and implemented for trade secret law and employs CATO's Factor model for representing and reasoning with cases. The cases are represented in terms of 26 Factors, prototypical fact patterns that tend to strengthen or weaken a plaintiff's claim (Ashley 1990; Aleven 1997). The Factors were derived from authoritative sources, like the Restatement of Torts, and from cases. Throughout this paper, we will use subscript π and δ to indicate which side is favored by a Factor. While trade secret law is a common-law domain and inherently case-based, there are some high level rules that define at an abstract level the relevant issues and requirements when plaintiff claims protection against trade secret misappropriation. The relevant sources are the Uniform Trade Secret Act, which has been adapted by various states, and the Restatement of Torts. They give the following definitions, respectively:

> "Trade secret" means information, [...] that:
>
> (i) derives independent economic value, [...] from not being generally known to, and not being readily ascertainable by proper means [...] and
>
> (ii) is the subject of efforts that are reasonable under the circumstances to maintain its secrecy.

> One [...] is liable [for trade secret misappropriation if]
>
> (a) he discovered the secret by improper means, or
>
> (b) his disclosure or use constitutes a breach of confidence [...]

These definitions can be translated into the high-level logical structure of the domain in Figure 1. With each of the five major issues, Info-Valuable, Maintain-Secrecy, Info-Used, Improper-Means, Confidential-Relationship, IBP associates from five to seven Factors. There is a causal relation between Factors and the respective issue, but this relation cannot be represented in a logical structure like the domain

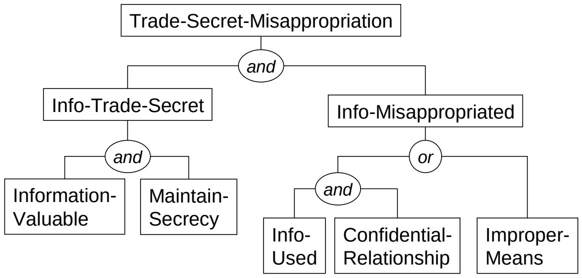

Figure 1: Logical structure for Trade Secrets law

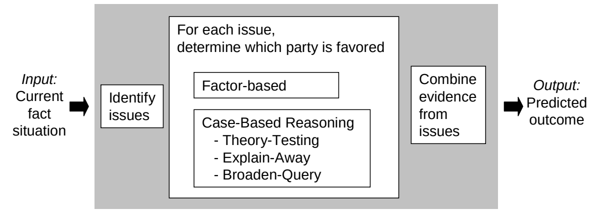

Figure 2: Overview of IBP's prediction process

model. The lists of Factors related to an issue have been identified manually after studying hundreds of trade secret law case opinions.

IBP's domain model is similar to CATO's Factor Hierarchy, which models the same area of law. CATO's representation, moreover, was a major motivation for our work on IBP. There are a number of differences, however. Most are caused by the different goals and tasks of the programs, and by some minor differences in personal interpretation of the domain. First and most importantly, IBP's domain model captures logical relations between the issues. The links between the nodes in the Factor Hierarchy represent an evidential support relation. Using its model in Figure 1, IBP performs logical operations, whereas CATO has a special inference mechanism to combine weak and strong links in the Factor Hierarchy for and against either side. Second, IBP's model has a different focus, it is limited to higher-level relations and does not have CATO's Factor Hierarchy's detailed representation of intermediate-level issues. In contrast to CATO, however, IBPs model links the highest level issues (Info-Trade-Secret and Info-Misappropriated) directly to case outcomes. Third, IBP's lists of issue-related Factors only include Factors that are at the core of the issues, whereas in CATO, even Factors with a more indirect connection are linked to issues.

Rule-base approaches (Waterman & Peterson 1981) differ from IBP's domain model in how the case facts are related to higher level issues and in what knowledge is represented. The rules in Waterman's system can be used to infer settlement values from the case facts and include expert heuristics. In IBP, on the other hand, the rules inherent in its domain model do not link the Factors in a rule chain to the case outcome. IBP's model captures definitions for when a plaintiff is entitled to protection for trade secret misappropriation, rather than expert heuristics.

IBP's domain model is also different from the representation in GREBE (Branting 1999), which uses rules and semantic networks. The most important distinction between the two approaches that IBP's task is prediction prediction, whereas GREBE's task is argumentation. The programs also in differ in how they integrate a domain model with cases. Using its detailed knowledge representation, which captures the facts as well as intermediate reasoning and conclusions for each case, GREBE can seamlessly integrate both reasoning modes. IBP, on the other hand, cannot rely on intermediate conclusions represented in its cases, and instead uses CBR methods like *Theory-Testing*.

Like GREBE, CABARET (Rissland & Skalak 1989) was designed for argumentation. Its reasoning is also based on a seamless integration of the reasoners at every step. While CABARET's cases, like IBP's, do not capture the court's reasoning, its intertwined reasoning was not designed for more modular reasoning, like in IBP's CBR methods, discussed next.

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3. IBP ALGORITHM

In making a prediction, IBP uses both its collection of cases and its model of the domain. As illustrated in Figure 2, IBP's prediction process can be broken down into three major steps, (1) identifying the issues in a case, (2) determining which party is favored for each issue, (3) combining the analysis of the issues. In determining which party is favored for an issue, IBP relies on the issue-related Factors when they all favor the same outcome. When the Factors favor both sides, however, it uses its case-based reasoning functions, which include THEORY-TESTING, EXPLAIN-AWAY and BROADEN-QUERY, to resolve conflicting evidence. Pseudocode for the algorithm is provided in the appendix.

We will discuss each of these steps in detail, and illustrate them with two examples, *The Boeing Company v. Sierracin Corporation*, 108 Wash.2d 38, 738 P.2d 665 (1987) (*Boeing*) and *K & G Oil Tool & Service Co. v. G & G Fishing Tool Service*, 314 S.W.2d 782 (*K&G*).

In *Boeing*, the plaintiff, Boeing, had developed an FAA-approved design for replacement airplane windows. The plaintiff was careful to guard the secrecy of its information. Outside suppliers who received copies of design drawings had to agree not to use the information for any purpose other than exclusive Boeing manufacture. The defendant had been one of those suppliers and had signed several non-disclosure agreements. All drawings that defendant had received were also stamped as confidential. After Boeing did not renew its contract with the defendant, the defendant tried to use plaintiff's drawings to get FAA-approval for its own windows.

In this case, several Factors favor the plaintiff, others favor the defendant. The plaintiff had disclosed the information to the defendant and to other suppliers, which is represented by the Factors $F1_\delta$, Disclosure-In-Negotiations, and $F10_\delta$, Info-Disclosed-Outsiders; both favor the defendant. However, the plaintiff's position is strengthened to the degree that he took several measures to keep the information secret, that the defendant agreed not to use or disclose the designs, that defendant knew that the drawings were confidential, because they were stamped, and that the disclosures to suppliers had been confidential. Therefore Factors $F6_\pi$, Security-Measures, $F4_\pi$, Nondisclosure-Agreement, $F21_\pi$, Knew-Info-Confidential, and $F12_\pi$, Out-

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Prediction for BOEING, which was won by PLAINTIFF
  Factors favoring plaintiff: (F21 F14 F12 F6 F4)
  Factors favoring defendant: (F10 F1)
```

(1) Factor-Based:

```
Issue raised in this case is INFO-USED
  Relevant factors in case: F14(P)
The issue-related factors all favor the outcome
PLAINTIFF.
```

(2) Theory-Testing:

```
Issue raised in this case is CONFIDENTIAL-RELATIONSHIP
  Relevant factors in case: F21(P) F4(P) F1(D)
Theory testing has clear outcome for PLAINTIFF.
  REINFORCED-MOULDING (F1 F4 F6 F8 F21 F15)
  DEN-TAL-EZ (F1 F4 F6 F21 F26)
  BRYCE (F1 F4 F6 F18 F21)
```

(3) Explain-Away:

```
Issue raised in this case is MAINTAIN-SECRECY
Relevant factors in case: F12(P) F10(D) F6(P) F4(P)
Theory testing has no clear outcome, try to explain
Away exceptions.
Cases won by plaintiff:
  FMC (F4 F6 F7 F10 F11 F12)
  TRANDES (F1 F4 F6 F10 F12)
Cases won by defendant:
  SCIENTOLOGY (F10 F12 F11 F6 F4 F20)
Trying to explain away exceptions favoring DEFENDANT
  SCIENTOLOGY can be explained away because of the
  unshared ko-factor(s) (F20).
Therefore, PLAINTIFF is favored.
```

(4) Combine-Analysis:

```
Outcome of the issue-based analysis:
   For issue INFO-USED, PLAINTIFF is favored.
   For issue MAINTAIN-SECRECY, PLAINTIFF is favored.
   For issue CONFIDENTIAL-RELATIONSHIP, PLAINTIFF
   is favored.

⇒Predicted outcome for BOEING is PLAINTIFF,
  which is correct.
```

Figure 3: IBP's analysis for *Boeing*, with annotations

side-Disclosures-Restricted apply. The fact that defendant used plaintiff's drawings corresponds to the pro-plaintiff Factor $F14_\pi$, Restricted-Materials-Used.

In $K\&G$, we focus on the issue whether the defendant had used the plaintiff's information. The relevant facts are as follows: The defendant had developed its own device after taking apart and reverse-engineering the plaintiff's device, even though he had signed a contract that he would not do so. The device developed by defendant was very similar to plaintiff's. The relevant Factors favoring the plaintiff in $K\&G$ are $F18_\pi$, Identical-Products, and $F14_\pi$, Restricted-Materials-Used. The defendant's position is supported by Factor $F25_\delta$, Info-Reverse-Engineered.

3.1 Identifying the Issues

Instead of trying to predict the outcome of a case by considering the evidence from all Factors at once, IBP identifies the issues raised in the case, and for each issue focuses on the relevant Factors.

Most cases in our collection involve only three or four issues. In some cases, for example, the parties do not dispute an issue, the court does not address it, and consequently, the case representation does not have any Factors related to that issue.

With *Boeing* as the current fact situation, IBP detects three issues: Info-Used (Factor $F14_\pi$), Confidential-Relationship (Factors $F1_\delta$, $F4_\pi$, $F21_\pi$), and Maintain-Secrecy (Factors $F4_\pi$, $F6_\pi$, $F10_\delta$, $F12_\pi$); see Figure 3, Nos. 1-3. *Boeing* does not have any Factors related to Info-Valuable, therefore IBP does not consider the issue. Defendant had learned the information in the course of a regular business relationship, there were no events related to improper means, and thus, the issue Improper-Means is also absent in *Boeing*.

3.2 Factor-Based

After the issues in the current fact situation have been identified, IBP analyzes which side is favored for each issue. If all issue-related Factors favor the same side, it infers that this side is favored on the issue.

In the example, *Boeing* has only one Factor, $F14_\pi$, Restricted Information-Used, related to the issue Info-Used. Since the factor favors plaintiff, all the evidence related to the Info-Used issue favors plaintiff. Thus, IBP concludes, the plaintiff will prevail on that issue; see Figure 3, Nr. 1.

3.3 THEORY-TESTING and EXPLAIN-AWAY

However, in many cases, conflicting evidence is found; some issue-related Factors may favor plaintiff, others defendant. Here, IBP performs what we call THEORY-TESTING, a technique based on scientific hypothesis testing. The program submits a query to retrieve all cases with the issue-related Factors from its case base. Intuitively, if all these case are won by the same side, there is good reason to believe that in the current fact situation, that side will prevail on the issue. More generally, when issue-related Factors can be found for both sides, there are two possible hypotheses which side should prevail. In THEORY-TESTING, the program reasons with the cases that share these Factors to determine which of the two hypotheses should be adopted.

Consider our example, the *Boeing* case, which has three issue-related Factors for Confidential-Relationship; see Figure 3, Nr. 2: $F1_\delta$, Disclosure-In-Negotiations, $F4_\pi$, Nondisclosure-Agreement, and $F21_\pi$, Knew-Info-Confidential. In IBP's collection, there are only three cases with these Factors: *Bryce*, *De-Tal-Ez*, and *Reinforced-Moulding*; all were won by the plaintiff. Thus, IBP infers that in the *Boeing* case, plaintiff was favored for the issue Confidential-Relationship.

The hypotheses evaluated in *Boeing* would be: Where the plaintiff voluntarily disclosed the information ($F1_\delta$), and where the defendant had signed a nondisclosure agreement ($F4_\pi$) and had been on notice that the information was confidential ($F21_\pi$), side X will prevail for the issue Confidential-Relationship. For the purpose of this analysis, IBP chooses the hypothesis that X is the side that won the cases retrieved by a query with the issue-related Factors.

When THEORY-TESTING returns cases favoring both sides, most often the majority of cases corresponds to one hypothesis, whereas a few cases are exceptions with the opposite outcome. This does not necessarily mean that there is no resolution; it is possible that the outcome of the exceptions was caused by facts unrelated to the current issue.

We found that some Factors, called KO-Factors (or Knock-out Factors), almost always dominate the outcome of a case. For instance, as an empirical matter, the plaintiff will not win a case with Factor $F20_\delta$, Info-Known. If the information is generally known, no matter how many security measures were taken, or how confidential the dealings between the parties, there is no trade secret to be misappropriated.

When IBP tries to EXPLAIN-AWAY exceptions to a theory, it tests whether KO-Factors like $F20_\delta$ are present in the exceptions, but absent in the current fact situation and in the other retrieved cases that conform to the theory.

For example, *Boeing* has Factors $F4_\pi$, Non-Disclosure-Agreement, $F6_\pi$, Security-Measures, $F10_\delta$, Info-Disclosed-Outsiders, and $F12_\pi$, Outsider-Disclosures-Restricted, related to the issue Maintain-Secrecy. The evidence on this issue is conflicting with Factors favoring both plaintiff and defendant. As with Confidential-Relationship, IBP tries THEORY-TESTING for Maintain-Secrecy; see Figure 3, Nr. 3. This time, one case, *Scientology*, was won by defendant, and IBP tries to EXPLAIN-AWAY that exception. It can use the KO-Factor $F20_\delta$ to distinguish *Scientology* from *Boeing*, *FMC* and *Trandes*. The result of EXPLAIN-AWAY is actually very reasonable when we look at *Scientology*, where the defendant won because of the KO-Factor $F20_\delta$, even though the plaintiff had maintained the secrecy of the information.

More formally, EXPLAIN-AWAY pursues the more probable hypothesis based on the cases returned by THEORY-TESTING and tries to salvage it by explaining away the counterexamples that are not consistent with this hypothesis. In the analysis of *Boeing*, the hypothesis would be: Where the plaintiff disclosed the information to outsiders ($F10_\delta$), but restricted these disclosures ($F12_\pi$), entered into a non-disclosure agreement with the defendant ($F4_\pi$), and took security measures ($F6_\pi$), side X should prevail for the issue Maintain-Secrecy. Here, IBP chooses as side X the side that won the majority of cases with the issue-related Factors, where the opposing cases could be explained away.

3.4 BROADEN-QUERY

THEORY-TESTING fails when the query based on the issue-related Factors is too specific and there are no precedents in the collection that share the issue-related Factors with the current fact situation. In this situation, IBP tries BROADEN-QUERY, a technique that leverages knowledge about what side is favored by the Factors. Consider the $K\&G$ case, which has three issue-related Factors for Info-Used: $F25_\delta$, Info-Reverse-Engineered, $F18_\delta$, Identical-Product, and $F14_\delta$, Restricted-Materials-Used, a set of Factors that is not found in any other case in our collection. Two of $K\&G$'s Factors favor the plaintiff; one factor, $F25_\delta$, favors the defendant. While we cannot count Factors to determine which side is favored, we know that the Factors in $K\&G$ represent a stronger scenario for the plaintiff than a hypothetical case that only has one of the pro-plaintiff Factors and the pro-defendant Factor. If in that hypothetical case the plaintiff prevailed, one could make the *a-forteriori* argument that in $K\&G$, the plaintiff has an even stronger position.

In BROADEN-QUERY, IBP "drops" each of the two Factors favoring plaintiff in turn[1], and carries out THEORY-TESTING for the hypothetical case. For $K\&G$, each of the two less constrained function calls to THEORY-TESTING retrieves one case that was won by the defendant; see *Technicon* and *Mineral-Deposits* in Figure 4. Thus, we can make an *a-forteriori* argument, that in $K\&G$, the plaintiff will prevail on the issue Info-Used.

[1]For ease of exposition, we restrict this discussion to the situation with two Factors favoring plaintiff, and one Factor favoring defendant. IBP can handle other situations as well; please refer to the algorithm outline in the Appendix for a more general formulation.

```
Prediction for KG, which was won by PLAINTIFF
  Factors favoring plaintiff: (F21 F18 F15 F14 F6)
  Factors favoring defendant: (F25 F16)
[…]
Issue raised in this case is INFO-USED
  Relevant factors in case: F25(D) F18(P) F14(P)
Theory testing did not retrieve any cases, broadening
the query.

For INFO-USED, the query can be broadened for PLAINTIFF.
Each of the pro-P Factors (F14 F18) is dropped for new
theory testing.
  Theory testing with Factors (F14 F25) gets the
  following cases:
  (TECHNICON PLAINTIFF F6 F10 F12 F14 F16 F21 F25)
  In this broadened query, PLAINTIFF is favored.
  Theory testing with Factors (F18 F25) gets the
  following cases:
  (MINERAL-DEPOSITS PLAINTIFF F1 F16 F18 F25)
  In this broadened query, PLAINTIFF is favored.
By an a-forteriori argument, the PLAINTIFF is favored
for INFO-USED.
[…]
=> Predicted outcome for KG is PLAINTIFF, which is correct.
```

Figure 4: Parts of IBP's Analysis for *K&G*

The implemented version of IBP requires that to be successful, at least one of the two function calls to THEORY-TESTING favor the plaintiff, and that none favor the defendant; otherwise BROADEN-QUERY explicitly abstains.

3.5 Combining the Analysis for the Issues

In the *Boeing* case, the plaintiff is favored on all issues raised in the case, thus, making the final prediction is straight forward. IBP predicts that the plaintiff wins, which is correct. In more detail, we can also infer that the information was a trade secret. As mentioned above, there were no Factors related to the issue Info-Valuable in *Boeing*, but we have evidence that the plaintiff's measures related to Maintain-Secrecy were sufficient. And, since the plaintiff is favored for Info-Used and Confidential-Relationship, we can conclude that the defendant misappropriated the information. Thus, the predication is that plaintiff should win a claim for trade secret misappropriation.

4. DETAILS OF THE ALGORITHM

4.1 KO-Factors

When IBP tries to explain away an exception, it is looking for convincing evidence why the exception did not have the same outcome as the other cases retrieved in THEORY-TESTING. So called Knock-out Factors (KO-Factors) used to distinguish the exception provide a good explanation the outcome, both in terms of the meaning and the number of past cases with the same outcome. That is, if (almost) every case where the Factor applies is won by the side it favors, we have good reason to believe that the Factor caused the outcome of the exception and that exception can be explained away on that basis. A Factor is only considered a candidate KO-Factor if at most 2 cases with the Factor were won by the opposite side. We also require that the meaning of the Factor be consistent with this explanation. For instance, Factor $F12_\pi$, Outsiders-Disclosures-Restricted, applies in 12 cases, all of which were won by the plaintiff. However, it is safe to assume that these outcomes were not caused by $F12_\pi$; this Factor tends to apply in cases that are otherwise very strong for the plaintiff. There are two kinds of Factors that can be KO-Factors. The first kind of KO-Factor represents facts that are contrary to the definition of a trade secret, called contra-definition. It expresses a clear violation of the requirements for a trade secret; see in Figure 1. The second kind of KO-Factor captures actions by the defendant that are either absolutely proper or strongly inappropriate. We refer to this as a good-actor/bad-actor Factor. Factor F20$_\delta$, which is used to explain away *Scientology* in the *K&G* example (see Figure 3), is a good example of a contra-definition Factor. If Factor F20$_\delta$ applies in a case, the information does not qualify for trade secret protection, and the defendant will win. F17$_\delta$, Independent-Development, is an instance of a good-actor/bad-actor Factor. If defendant can show that its product is the result of its own, honest research and development, it has a "good actor" affirmative defense against plaintiff's claim.

4.2 Weak Factors

While the KO-Factors are very powerful, there are also Factors with very little predictive strength. These Factors are important for the outcome of a case, in particular in the context of other Factors. In isolation, however, they may not provide sufficient evidence for issue-based prediction. Consider Factor F10$_\delta$, Info-Disclosed-Outsiders, which applies for instance when the plaintiff disclosed the secret information to a contractor or supplier. While this is evidence that the plaintiff did not keep the information perfectly secret, one cannot conclude just based on the presence of Factor F10$_\delta$ that the plaintiff failed to take security measures, and that the defendant is favored for the issue Maintain-Secrecy. In fact, such disclosures may well be common in the business, and mae with the understanding that the supplier has to treat the information as confidential.

In IBP, we therefore do not take the presence of an isolated weak Factor as sufficient evidence related to an issue. Instead, we treat the issue as if there was no Factor related to the issue. In order to identify weak Factors, we take the meaning of the Factor into account and focus on the odds of the favored side winning, compared to the baseline; see Table 1, Nr. 11. For all weak Factors that we have identified, the odds are less than 20% over the baseline.

From a machine learning viewpoint, this raises the question whether weak Factors should be taken into account at all. However, both from a statistical and from an AI perspective, even the weak Factors are relevant for reasoning about the outcome of cases. First, for all 26 Factors, the probability of the favored side winning given that the Factor applies is higher than the baseline. Statistically, every Factor is positively related to the side it favors. Second, a case is not a collection of unrelated features; the context of the Factors is important. By removing a Factor, the overall gestalt of the cases would be changed in an inappropriate way.

4.3 Abstentions and Absence of Issue-Related Factors

Even with IBP's EXPLAIN-AWAY and BROADEN-QUERY, it sometimes remains impossible to resolve conflicting evidence for some cases. In those cases, IBP abstains on the issue. An abstention usually means that evidence for both sides was found or that the evidence was not conclusive.

When it comes to combining the outcome from the issue-based analysis following Figure 1, we consider abstentions in the "and" as follows: If plaintiff was favored for one issue, and there was an abstention on another, the combined result is an abstention (since we cannot rule out that the defendant may prevail). If the defendant was favored on an issue, and there was an abstention on another, the combined result is an abstention (since even if the plaintiff prevails on the issue, the defendant is still favored in the combination).

5. RELATION TO CATO AND HYPO

5.1 Background

THEORY-TESTING and EXPLAIN-AWAY were motivated by a pedagogical tool with the same name from the CATO instruction (Aleven 1997). In CATO's workbooks, students were given a general proposition in trade secret law, and asked to come up with their own prediction. They translated the proposition into CATO's Factor representation and retrieved the relevant cases. Depending on the outcome of the query, the students were encouraged to explain why their prediction was not confirmed by the retrieved cases, to read the summaries of cases that did not fit their theory, or to modify their query if it retrieved too few or too many cases. CATO's theory-testing was never automated, however, and it has not been linked to issues as in IBP.

THEORY-TESTING and EXPLAIN-AWAY are also related in interesting ways to Hypo's and CATO's argument concepts. IBP's reasoning is focused on the issue-related Factors, and for the purpose of this paper, we will use the term issue-specific claim lattice to refer to a claim lattice that only takes the issue-related Factors into account.

With respect to an issue, the cases retrieved by THEORY-TESTING are what we call *maximally-on-point*, that is, they are most on point and they share all of the (issue-related) Factors with the current fact situation; in other words, they are in the same node as the current fact situation in the issue-based claim lattice. If all maximally-on-point cases favor one side, then this side certainly has the stronger argument (with respect to the issue).

EXPLAIN-AWAY is a way of distinguishing cases, very similar to what is done in CATO. IBP can explain away exceptions with Factors that favor the exceptions' outcome and that are absent in the current fact situation and the other cases retrieved by THEORY-TESTING. Notice that EXPLAIN-AWAY is not limited to issue-related Factors. In fact, often KO-Factors that are unrelated to the current issue will be the basis for explaining away. Unlike CATO, however, IBP's reasoning does not involve downplaying or emphasizing.

Finally, BROADEN-THEORY can be compared to reasoning with most-on-point cases in an issue-specific claim lattice. Instead of focusing on the maximally-on-point cases, as in THEORY-TESTING, IBP reasons with a subset of the most-on-point cases. To make an *a-forteriori* argument for a side, it only considers those branches that share conflicting Factors with the root node, though. In Figure 5, IBP focuses on Nodes 1 and 2. Node 3 is not very useful for our goal, resolving conflicting evidence, because it only shares the two pro-plaintiff Factors with *K&G*. Even though all cases in that node were won by plaintiff, Factor F25$_\delta$ could be used in an argument distinguishing *K&G* from *Data General, Solo-Cup* and *Tri-Tron*.

5.2 Prediction using CBR in CATO and HYPO

IBP is not the only way to combine predictive and normative information in order to improve prediction. Aleven

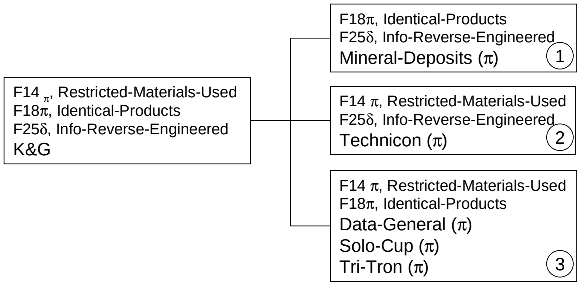

Figure 5: Issue-based claim lattice for *K&G*

(2003) has explored the use of argument concepts for prediction. His experiments explored the connection between prediction and argumentation from a somewhat different angle, by testing whether focusing on the most relevant cases for argumentation would also be useful for predicting case outcomes. The prediction methods are based on the following decision rule:

If all cases that satisfy a relevance criterion R
were won by the same side,
then predict that side,
else abstain.

The reported experiments were fairly extensive; here, we will focus on two relevance criteria. First, the HYPO-BUC algorithm used concepts from the original HYPO model. Prediction was based on the set of best untrumped cases. While this algorithm made very few mistakes, it also abstained frequently. The major shortcoming of the HYPO-BUC criterion is that it only takes shared Factors into account; it does not consider distinctions, extra Factors present in the retrieved cases, which probably caused many of the abstentions. This problem can be addressed by using argument concepts from CATO in the relevance criterion. The NoSignDist/BUC algorithm added knowledge about the domain from CATO's Factor Hierarchy in a two-step process to retrieve the most relevant cases. It collects all cases that are citable and have no significant distinctions, meaning that no distinction can be emphasized and all distinctions can be downplayed. Among those, it selects the cases that are most on point and untrumped. This method made more mistakes than the HYPO-BUC prediction, but also had by far fewer abstention; see Table 1, Nr. 3.[2] The difference between HYPO-BUC and NoSignDist/BUC is statistically significant. This experiment shows that adding normative or background knowledge from the Factor Hierarchy can lead to better prediction.

6. EXPERIMENTS

6.1 Experiment Setup

In order to evaluate the performance of IBP, we ran a number of experiments, which are summarized in Table 1. In addition to CATO's existing Case Database of 148 cases, we added 38 new cases for the evaluation. The majority of these new cases had been selected and their factors marked up for a different purpose and before IBP was conceived, but they were entered after the implementation of IBP was completed. The cases came from state and federal courts of different jurisdictions. Of the 186 cases, 108 were won by the plaintiff, 78 by the defendant.

	Algorithm	corr.	err.	abst.	acc.	p
1	IBP	170	15	1	0.914	n/a
2	Naive Bayes	161	25	0	0.865	0.03
3	NoSignDist/BUC	152	19	22	0.778	0.00
4	C4.5-pruned	158	28	0	0.849	0.01
5	C4.5-rules	155	31	0	0.833	0.01
6	Ripper	154	32	0	0.828	0.00
7	IB1	153	33	0	0.823	0.00
8	HYPO-BUC	127	9	50	0.683	0.00
9	IBP-model	99	15	38	0.726	0.00
10	IB3	96	52	0	0.649	0.00
11	Baseline	108	78	0	0.581	0.00

Table 1: Experimental results

6.2 Comparison

We first compared IBP to a number of easily accessible, standard machine learning algorithms. They are: Ripper (Cohen 1995), a rule learning algorithm; C4.5 (Quinlan 1993), a decision tree learning algorithm that can derive rules by pruning; Naive Bayes (Mitchell 1997)[3]; and IBL, a collection of case-based learning algorithms (Aha 1991). All algorithms were tested in a leave-one-out cross-validation. We kept the default parameter settings for the algorithms.

IBP correctly predicted the outcome of 170 cases, made 15 errors, and abstained once, which corresponds to an accuracy of 91%. None of the other algorithms reached IBP's accuracy; Naive Bayes came closest with 86% accuracy. In addition to the evidence in table 1, which shows that IBP got more predictions correct than any other algorithm, we wanted to make sure that these differences can really be attributed to differences in the algorithms. We used McNemar's test (Ditterich 1996) to find out whether the observed difference between IBP and the algorithm performance is statistically significant. This is a non-parametric test which is particularly suited to compare two algorithms. Its inputs are two numbers, namely, for each of the two algorithms that are compared, how many examples this algorithm gets correct, when the other one makes a mistake. We adapted it to deal with abstentions by IBP and the HYPO/CATO based algorithms, by counting an abstention like a correct prediction of one algorithm, if the other algorithm made a mistake. We found that for every algorithm in our experiment, the difference between IBP and that algorithm was statistically significant; see rightmost column with the p-values in Table 1[4]

6.3 Relative Importance of Model and Cases

It is an interesting question whether to credit IBP's performance to its model or to its CBR component. In an

[2]Notice that these results are not exactly the same as those reported in (Aleven 2003); we used the same program, but slightly different cases.

[3]We used Ray Mooney's Lisp implementation.

[4]The p-value indicates the probability that the observed difference between two algorithms is just caused by random variations in the data, so a low p-value is good. Generally, $p < 0.05$ is considered convincing evidence that there is a true difference between the algorithms.

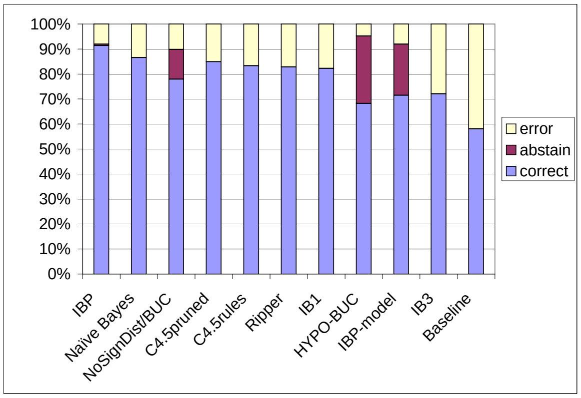

Figure 6: Overview of experimental results

experiment, we disabled Theory-Testing, Explain-Away and Broaden-Query, and ran the prediction for the entire collection. This caused IBP to abstain on 37, or 20% of the cases, but it did not effect the number of errors; see Table 1, Nr. 9. It is remarkable that the CBR component *always* leads to a correct prediction. IBP is yet another example of the 80-20 rule: About 20% of the effort (for the issue-based analysis) accounts for 80% of the performance. Much more work is required to get the remaining 20% right.

Likewise, relying solely on reasoning with cases for prediction also does not work as well as IBP. Hypo-BUC is a purely case-based prediction algorithm, which like IBP's CBR component is based on Hypo's argument concepts. While Hypo-BUC makes fewer mistakes than IBP, it abstains in more than 25% of the cases. This indicates that prediction based on reasoning with the cases alone can account for at most 75% IBP's performance.

To summarize, IBP's combination of cases and domain model performs better than prediction based on either component alone.

One may also ask whether relying on CBR concepts that were developed for argumentation may have a negative impact on prediction based on cases. In our experiments, we compared IBP to a set of purely case-based algorithms from the IBL package (see Table 1, Nos. 7 and 10). IB1 is a case-based or lazy learning algorithm and uses a nearest neighbor approach. IB1 gets 82% accuracy, compared to IBP's 91%. The results of IB1 suggest that relying solely on the cases can lead to good accuracy, but prediction accuracy is better with the knowledge from IBP's weak model.

Finally, we explored whether a "better" case-based algorithm would lead to better prediction, even without adding a weak model like in IBP. In our experiment, the methods based on HYPO and CATO abstain frequently, and one can hypothesize that this may be caused by some form of noise in the data. Thus, we tried IB3, which is a variation of IB1 designed to deal with noisy data. At first glance, IB3 may sound promising for legal cases, in particular given that we may well have some form of bias in the selection of our cases. However, the experimental results show that IB3's performance is significantly worse that IB1. One reason may be the definition of what is considered noise. We are trying to predict the outcome of real legal cases, which are inherently noisy and not consistent from a machine learning point of view; what may look like an exception in machine learning is often an apparently binding, legally relevant precedent.

6.4 Anomalous Cases

Finally, we analyzed those cases for which multiple algorithms made incorrect predictions. We found that there are several reasons why certain cases are hard to predict.

First, sometimes the court's reasoning and reconciliation of strengths and weaknesses is peculiar to a particular case making it virtually impossible to infer its outcome. A case on which every algorithm in our experiment made a mistake is *Franke v. Wiletschek*, 209 F.2d 493 (2nd Cir. 1953). In this case, the judge considered the defendant's behavior so outrageous, that he ruled for the plaintiff, even though there was evidence the plaintiff's information did not meet the requirements for a trade secret. If we changed our model (Figure 1) to fit *Franke*, IBP's performance would deteriorate drastically. Likewise, *Goldberg v. Medtronic*, 686 F.2d 1219 (7th Cir. 1982), causes many algorithms to make an incorrect prediction. Here, too, the court ruled for the plaintiff, even though the information had been generally known and had been disclosed to third parties, because there was a very strong confidential relationship between the parties. As in *Franke*, the Factors of the case do not reflect this reasoning. Apparently, other judges are more in line with IBP's model; a subsequent decision criticized the *Goldberg* decision and the case is yellow-flagged in the Westlaw database. The court in *Wexler v. Greenberg*, 399 Pa. 569, 160 A.2d 430 (1960) argued that since the defendant was the sole developer of the information, he did not have a duty to keep the information confidential. We did not observe this argument in any other case. When we tried to improve IBP so that it would capture some of the reasoning of the *Wexler* court, we found that IBP correctly predicted *Wexler*, but actually made more mistakes for the rest of the cases. To summarize, we found that in some decisions the court assigns exceptionally high importance to a particular fact, and to the degree that there are no features that could be used to predict such judgments and preferences, these cases will not be predicted correctly.

Second, in very rare cases, a decision may be criticized for not being correct. As mentioned above, *Goldberg* is yellow flagged, which means a court in a later decision did not agree with the *Goldberg* court's reasoning. *Corrosion v. Dicharry*, 631 So. 2d 1389, is another case that stood out as being exceptionally hard to predict. It has a dissenting opinion that we found more convincing than the ruling opinion. We added both to our collection, the ruling opinion, and the dissenting opinion, which argued for the opposite outcome and identified additional Factors. In our experiments, every algorithm predicted the outcome recommended by the dissent rather than that assigned by the majority opinion. This combined evidence suggests that in some cases, the courts may "not get it right," which makes the outcome of those cases impossible to predict correctly.

Third, while the Factors are well-defined, there is still some room for interpretation which Factors should apply to a case. For instance, in a number of cases, it is debatable whether CATO's Factor $F19_{\delta}$, Security-Measures, should apply. This Factor has been assigned in *Allen Manufacturing Company v. Loika*, 145 Conn. 509, 144 A.2d 306 (1958), because the plaintiff had only taken minimal measures to protect the information, and had left many gaping security holes. However, the court decided that even the minimal measures were sufficient. On the other hand, in *Junkunc v. S.J. Advanced Technology and Manufacturing Corp.*, 149 Ill.App.3d 114, 498 N.E.2d 1179, 101 Ill.Dec. 671, the plaintiff took several, albeit isolated measures to maintain the secrecy of the information. Since the court explicitly listed these measures, the case representation contains $F6_{\pi}$, Security-Measures. The court, however, placed more weight on the several security holes, which favored the defendant.

Fourth, even though the Factor representation is very powerful, it still does not capture every aspect of a case. In *Burten v. Milton Bradley Co.*, 763 F.2d 461, the plaintiff had submitted a proposal for a board game to the defendant, a toy manufacturer. At the same time, plaintiff signed a form that the disclosure had been voluntary and that no relationship was implied between the parties. The defendant rejected the idea, but one year later, came out with its own game, very similar to plaintiff's. Here, the court ruled that even though the plaintiff had signed a waiver of confidentiality, there was a confidential relationship between the parties, because the signed agreement had been too vague. The CATO representation has a Factor for confidentiality waivers, Factor $F23_{\delta}$, but it cannot capture whether such an agreement is sufficiently specific. All algorithms in our experiment made an incorrect prediction for *Burten*. Unlike Hypo's representation, Factors also do not capture the magnitude of the underlying facts. In many cases in our collection, like in *Smith v. Dravo Corporation*, 203 F.2d 369 (7th Circuit), Factor $F16_{\delta}$ applies when the information could be duplicated after a certain effort. In *Speciner v. Reynolds Metals Company*, 279 F.2d 337 (2nd Cir.1960), on the other hand, the information was clearly disclosed by the marketed product, and only minimal effort was required to reverse-engineer the product. This exceptional strength and importance of Factor $F16_{\delta}$, which was the main reason why defendant won, could not be inferred from the Factor representation. Several algorithms correctly predict *Dravo*, but make a mistake for *Speciner*.

To summarize, there are several reasons why it is hard to predict certain cases. Some cases, like *Burten*, could perceivably be addressed by continuously amending the representation, whereas others, like *Franke*, will probably remain beyond the scope of practical and implemented AI programs.

7. CONCLUSIONS

In this paper, we introduced IBP, a novel algorithm that combines reasoning with an abstract domain model and case-based reasoning techniques to predict the outcome of case-based legal arguments.

We have presented an empirical evaluation of IBP, in which we compare our algorithm to prediction based on Hypo's and CATO's relevance criteria, and to a number of widely used machine learning algorithms. IBP reaches higher accuracy than all competitors, and hypothesis testing shows that the observed differences are statistically significant. We also carried out an ablation study, which indicated that both sources of knowledge in IBP contribute to the accuracy of its predictions.

Unlike the predictions generated by machine-learning or statistical techniques, IBP's predictions are accompanied by explanations (see the program output in Figure 3) as are those reported in (Aleven 2003). The CATO-based predictions are explained in terms of CATO's argument moves. By contrast, IBL's explanations summarize the results of testing theories about a new case from the viewpoint of the relevant issues. Both kinds of explanations are a useful way of interpreting the meaning of a prediction.

Our experiments confirm that predictions of case outcomes based on the data in case-based legal reasoning models are not only possible but can be of high quality, at least relative to the data in the model. It remains to assess the quality of the predictions in the real world, which presumably requires a much larger sampling of trade secret cases. The implications are far-reaching, especially as researchers respond to the challenge of (Hafner & Berman 2002) and push CBR representations to reason with more abstract normative concepts such as purposes and values. The recent work of (Bench-Capon & Sartor 2001) and (Horty 1999), for instance, explores ways in which preference rules or other techniques based in part on values can determine the normative outcome of an argument.

Where data is available, however, namely substantial numbers of cases represented by factors and issues, it may be at least as productive to employ IBL's predictive techniques (i.e., theory testing, explaining away, and broadening a theory) to predict outcomes. IBL's outcomes are empirical, to be sure, but normative information has been integrated into generating and explaining them. As the discussion of anomalous cases suggests, we are in the process of identifying criteria for determining when normative decisions are anomalous (Ashley 2002) and consider how changes in the model, or in ones representation of a case, affect the model's predictions, and thus its coherence as a model of a legal domain.

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APPENDIX

A. OUTLINE OF IBP ALGORITHM WITH SUBFUNCTIONS

```
function IBP (cfs) returns predicted outcome
    issues ← issues raised in cfs
    for each issue
        collect (issue, ISSUE-ANALYSIS) into analysis
    return COMBINE-RESULTS(analysis)

function COMBINE-RESULTS (analysis)
    if INFO-TRADE-SECRET?(analysis) returns defendant
      or INFO-MISAPPROPRIATED?(analysis) returns
      defendant
      then return defendant
      elsif INFO-TRADE-SECRET?(analysis) returns
            abstain
            or INFO-MISAPPROPRIATED?(analysis) returns
            abstain
            then return abstain
            else return plaintiff

function ISSUE-ANALYSIS(case,issue)
    issue-related-factors ← factors in case related to issue
    if all issue-related-factors favor the same side
      then return that side
    elsif there are cases where the issue-related-factors apply
      then return the result of THEORY-TESTING
            with issue-related-factors
    else return the result of
      BROADEN-QUERY(issue-related-factors)

function THEORY-TESTING(factors)
    if all cases retrieved by query for factors favor the
      same side
      then return that side
    else return the outcome of
      EXPLAIN-AWAY(retrieved cases, cfs, factors)

function EXPLAIN-AWAY(retrieved cases, cfs, factors)
    theory ← outcome of majority of retrieved cases
    exceptions ← retrieved cases opposite to theory
    if all exceptions are DISTINGUISHABLE from cfs and
      from retrieved cases that follow theory
      then return theory, else return abstain

function DISTINGUISHABLE(exception, cases, theory)
    if exception has KO-Factors that do not apply in cases
      and that can cause an outcome opposite to theory
      then return true, else return false

function BROADEN-QUERY(factors)
    side ← side favored by majority of factors
    pro-side-factors ← factors favoring side
    if there is a pro-side-factor for which DROP-FACTOR
      still favors side
      and there is no pro-side-factor for which
      DROP-FACTOR favors opposite of side
      then return side, else return abstain

functionDROP-FACTOR(factor, factors)
    remaining-factors ← REMOVE(factor, factors)
    return result of THEORY-TESTING(remaining-factors)

functionINFO-TRADE-SECRET?(analysis)
    relevant-issues → {Info-Valuable, Maintain-Secrecy}
    if defendant is favored for any relevant-issue
      then return defendant
    elsif there is abstain for any relevant-issue
      then return abstain
```