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Abstract. Online dispute resolution is becoming the main method when dealing with a conflict in e-commerce. Our framework exploits the argumentation semantics of defeasible logic which is proved to be the most suitable choice for legal reasoning The contribution here consists in combining rough set theory with defeasible logic in order to handle the gradual information to be revealed in a legal dispute. Such a framework covers both aspects of the law: case based reasoning and legal syllogism.

1 Introduction

Online Dispute Resolution (ODR) promises to become the predominant approach to settle e-commerce disputes. To reach this statute it needed ten years of fast and sustained development [1]: starting in 1996 as a hobby, an experimental stage sustained by academics and non-profit organizations during 1997-1998, an entrepreneurial stage from 1999 (the rate of success as business is 75%), and beginning with 2003 there have been much governmental effort to institutionalize the online dispute resolution process.

Our goal is to provide a flexible decision support framework, according to the current practice in law, with potential benefits to the e-commerce and legal communities [2, 3]. Flexibility in configuring ODR systems is both an opportunity and a challenge. The opportunity is that any business can, quite quickly, have its own "court" specialized in disputes that might occur in its specific business domain. The challenge is that the technical instrumentation must simultaneously satisfy the business viewpoint asking for trust [4] and the legal viewpoint, which requires accordance with the current practice in law. One aspect covers how to combine different knowledge sources such as the legal framework, contractual clauses, and data representing precedent litigation cases in order to assist de resolution process.

[5]

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We base our framework on rough set theory and defeasible logic, enriched with level of certainty to handle practical scenarios. In the next section we formalize the argumentation framework by defining both sustaining and defeating rules for a claim.

2 Argumentation Framework

Our framework exploits the argumentation semantics of defeasible logic which is proved to be the most suitable choice for legal reasoning [6]. A theory in defeasible logic is a structure $\langle F,\ R\rangle$ formed by a finite set of facts $f(\beta) \in F$, and a finite set of rules $r(\gamma, cov) \in R$, having the *certainty factors* β, γ and the *coverage factor* $cov \in [0..1]$. A fact $f(\beta) \in F$ is *strict* if $\beta = 1$ and *defeasible* if $\beta < 1$. The rules are split in two disjoint sets: the set of support rules R_{sup} which can be used to infer conclusions and the set of defeaters R_{def} that can be use only to block the derivation of some conclusions. A rule $r(\gamma, cov) \in R_{sup}$ is *strict* if and only if $\gamma = 1$. The set of strict rules is represented as $R_s = \{r(\gamma) \in R_{sup} | \gamma = 1\}$. A rule $r(\gamma) \in R_{sup}$ is *defeasible* if and only if $\gamma < 1$. The set of defeasible rules is represented as $R_d = \{r(\gamma) \in R_{sup} | \gamma < 1\}$. Strict rules are rules in the classical sense, that is whenever the premises are indisputable, then so is the conclusion, while defeasible rules are rules that can be defeated by contrary evidence. Defeaters are rules that cannot be used to draw any conclusions, their only use is to prevent some conclusions. A defeasible conclusion q can be defeated either by inferring the opposite one $\sim q$ with a superior certainty factor (rebuttal defeater), or by attacking the link between the premises and the conclusion q (undercutting defeater[1]). The problem is rised by the fact that a defeater of the consequent q attacks all rules which sustain q and there is no mean to attack a single rule sustaining the respective conclusion. To handle this we introduce negated rules. We will use the following notations: $\not\rightarrow$ for $\neg\ (a \rightarrow b)$, with semantics "a does not strictly determines b", $\not\Rightarrow$ for $\neg\ (a \Rightarrow b)$, with semantic "a does not defeasible determines b", and $\not\rightsquigarrow$ for $\neg\ (a \rightsquigarrow b)$ with semantics "a does not defeat b". We note by R_{ns} the set of negated strict rules, by R_{nd} the set of negated defeasible rules, and by R_{ndef} the set of negated defeaters.

The existence of negated rules introduces two advantages. Firstly, such a logic which defines pairs of relations provides symmetrical means of argumentation for both disputants. The type of counterargument depends on the type of the current sentence φ: fact, support rule, defeater (table 1). Here A represents the set of antecedents sustaining q and X represents a different set of premises supporting the opposite conclusion. The sentence *"A defeasible implies q" ($A \Rightarrow q$)* can be attacked either by i) simple claiming the opposite fact $\neg q$, ii) deriving (stricly or defeasible) the opposite conclusion based on a different set of premises X ($X \rightarrow \neg q$, $X \Rightarrow \neg q$), iii) blocking the derivation of the consequent ($X \rightsquigarrow \neg q$), or iv) claiming the set A is not suffice to sustain the consequent q ($A \not\Rightarrow q$).

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[1] Intuitively, an undercutting defeater argues that the conclusion is not sufficiently supported by its premises.

Table 1. Attacking a sentence φ depends on its type.

φ	$\sim\varphi$
q	$\neg q$, $X \rightarrow \neg q$, $X \Rightarrow \neg q$
$A \rightarrow q$	$\neg q$, $X \rightarrow \neg q$, $A \not\rightarrow q$
$A \Rightarrow q$	$\neg q$, $X \rightarrow \neg q$, $X \Rightarrow \neg q$, $X \leadsto \neg q$, $A \not\Rightarrow q$
$A \leadsto q$	$A \not\leadsto q$
$A \not\rightarrow q$	$A \rightarrow q$
$A \not\Rightarrow q$	$A \Rightarrow q$
$A \not\leadsto q$	$A \leadsto q$

Defeaters are convenient to represent exceptions, while negated rules to model counterexamples.

3 From Data to Defeasible Theory

Consider an e-commerce dispute scenario where the initial information provided by the plaintiff reveals that the item was delivered in time, but supplementary charge has occurred. He also didn't sign any clause regarding another remedy in case of a dispute issue, therefore he considers that he has the right to claim money back.

Collecting similar cases. The first phase consists in collecting all the cases with the similar attributes and the respective remedy in each case. The decision table we consider consists in 98 cases of dispute resolutions (table 2). The condition attributes regards the payment arrangements, the existence or not of a contractual clause stipulating that no refund will be considered, but only the item replacement, and the delivery status,. The column labeled "remedy" contains the output of the resolutions, while N represents the number of similar cases, as regard the considered attributes.

Table 2. Dispute resolution cases for the *refund* claim.

#	**payment**	**contractual_clause**	**delivery**	**remedy**	**N**
1	supplementary charge	yes	partial	refund	8
2	incorrect price	yes	on time	refund	10
3	supplementary charge	no	on time	refund	4
4	initial price	yes	partial	no refund	50
5	incorrect price	no	delayed	refund	6
6	supplementary charge	no	on time	no refund	20

The current level of abstraction contains inconsistent data: facts 3 and 6 where the same premises implied opposite decisions. These cases contains hidden reasons which has influenced the outcome and which may be revealed in case of a low level dispute analysis. At this phase, the attributes *payment*, *contractual_clause*, and *delivery*[2] describe the set of refund decisions approximately. Under the rough set theory the next approximations follow. The lower approximation $B_a = \{1, 2, 5\}$ represents the maximal set of facts that can certainly be classified as with the refund outcome. The upper approximation $B^a = \{1, 2, 5, 3, 6\}$ contains the possible cases where the refund decision might be taken. The difference $B^a \setminus B_a = B = \{3, 6\}$ is called boundary region of the set $\{1, 2, 3, 5\}$ in which the refund decision was taken. A set is rough if its boundary region is not empty [7].

Computing the reducts. The next step in data analysis is to find a minimal subset of data that preserves the degree of consistency. This reduct represents the essential data used to derive the corresponding defeasible theory. Following [7], table 3 presents one such reduct.

Table 3. Dispute resolution cases with consistency.

#	payment	contractual_clause	remedy	N
1'	supplementary charge	yes	refund	8
2'	incorrect price	-	refund	10
3'	supplementary charge	no	refund	4
4'	initial price	-	no refund	50
5'	incorrect price	-	refund	6
6'	supplementary charge	no	no refund	20

Every fact in the data table determines a decision rule. For instance the fact 1' is synonym with the rule r'_1 : *supplementary_charge* $\wedge$ *contractual_clause* $\Rightarrow$ $refund$. In order to provide explanation of decisions in terms of conditions one can define inverse decision rules [7]: r''_1 : $refund$ $\Rightarrow$ *supplementary_charge* $\wedge$ *contractual_clause*. Explanation capabilities are necessary [4] in such a dispute resolution system as a mean to provide trustworthiness in the outcome.

Introducing defeasible rules. We use the conditional probabilities in [7] to derive defeasible rules. The *support* of a rule $r : p \Rightarrow q$ represents the number of cases in the decision system that poses both properties p and q, p being a

[2] The report *The European Online Marketplace: Consumer Complaints 2005* conveyed that 46% of the complaints regard delivery issues, 8% payment arrangements, and 8% quality of the items.

conjunction of premises. The certainty factor represents the accuracy of the rule $p \Rightarrow q$ and it is defined as $\gamma(r) = \gamma(q|p) = support(p,q)/support(p)$. The coverage factor reflects how well a specific case is replicable $cov(r) = cov(p|q) = support(p,q)/support(q)$. The certainty factor helps us to introduce defeasible logic. A rule with $\gamma = 1$ defines a strict rule. A rule with $\gamma < 1$ defines a defeasible rule. Strict rules acts in the lower approximation region, while defeasible rules in the boundary region. When new information is available, it guides the process into a refined stage. The new facts are modeled with defeaters (rebuttal, undercutting or negated rules), which may block the derivation of some defeasible conclusions. In the rough set interpretation, the initial boundary region will be adjusted according to the new information. The defeaters semantics helps to adapt the model built so far in order to deal with new information. Thus, an inccorrect classification in the boundary region can be challenged by an undercutting defeater which attacks the link between the premises and the conclusion. From table 3 the pairs $< \gamma, cov >$ are computed for each rule[3]. Figure 1 illustrates the corresponding defeasible theory for the current reduct[4], where "$\rightarrow$" models strict rules and "$\Rightarrow$" defeasible ones.

$$
\begin{array}{l}
r'_1(1, 0.29) : supplementary\_charge, contractual\_clause \rightarrow refund \\
r'_2(1, 0.57) : incorrect\_price \rightarrow refund \\
r'_3(0.27, 0.14) : supplementary\_charge, contractual\_clause \Rightarrow \neg refund \\
r'_4(1, 0.71) : supplementary\_charge \rightarrow refund \\
r'_6(0.83, 0.29) : supplementary\_charge, contractual\_clause \Rightarrow \neg refund
\end{array}
$$

Fig. 1. Defeasible theory

Handling exceptions. Usually the rules that apply to only few cases are seeded out [9]. In our approach marginal rules can be seen rather as exceptions and modeled with defeaters. When a court distinguishes a case it points to some

[3] The number of all cases satisfying the decision attribute $refund$ is 8+1+4+6=28, while for $\neg refund$ is 20+50=70. Each judicial case has some metadata attached, such as court which filed the case or data of judgement. The indiscernability relation of the cases in the rough set approach can be considered both as regard attributes of the case and these matadata. In the above computation, we consider all the cases having the same relevance. By taking metadata into consideration, one can introduce legal strategies such as *legis posterior* or *legis superior* into the algorithm. Under the *legis posterior* doctrine, instead of simply counting cases, one may compute a weighted sum with the contribution of each case accrodingly to its age. Accordingly to the *legis superior* principle, the outcome imposed by the strongest court takes precedence when computing the certainty factor of a defeasible rule.

[4] A reduct is not unique. The frequence of the rules generated from all the computed reducts can be used to define an importance measure of the rule as in [8].

features that makes that case different. If we can find such attributes for a particular case, we can formalize it with undercutting defeaters. In the situation it cannot be distinguish by the precedent case it remains a counterexample. Here, the marginal rules are given by the converage factor. If we establish a threshold of 0.2 only rule 3' with a $cov = 0.14$ is considered marginal. For this particular rule, suppose that 3 out of the $N = 4$ cases in figure 2 have, compared to the rule 6', a supplementary attribute *item_broken_by_the_client* (not used in the first phase of approximation). This exception is modeled with the undercutting defeater r'_{31}, which has the certainty factor $3/4 = 0.75$ and the coverage $1/28 = 0.035$. For the remaining rule of the $N = 4$ cases there is not known any distinguish attribute. Therefore it represents a counter-example and it is modeled with the negated rule r'_{32} (figure 2). Observe that the certainty factor of the rule r'_6 was

$r'_1(1, 0.29) : supplementary\_charge, contractual\_clause \rightarrow refund$
$r'_2(1, 0.57) : incorrect\_price \rightarrow refund$
$r'_{31}(0.75, 0.035) :\succ item\_broken\_by\_the\_client \rightsquigarrow refund$
$r'_{32}(0.127, 0.105) : supplementary\_charge, contractual\_clause \not\Rightarrow \neg refund$
$r'_4(1, 0.71) : supplementary\_charge \rightarrow refund$
$r'_6(0.873, 0.29) : supplementary\_charge, contractual\_clause \Rightarrow \neg refund$

Fig. 2. Handling exceptions and counterexamples.

increased. This covers the idea in common low that exception proves the rule in the case not excepted[5]. Note also, the high confidence assigned to the defeater r'_{31}, value which reflects one of the legal principles for conflict resolution, known as *legis specialis*[6].

4 Mediation for ODR

Mediators have varying disponibility to accept as evidence the facts conveyed by the disputants. Taking such judicial decisions the next four components are relevant: the inference method, the minimul level of certainty required to accept evidence, the selection of relevant arguments, and the derivation of the outcome.

4.1 Inference rules in argumentation

Given a conclusion q that can be derived based on strict premises in the rule $r[\gamma]$, meaning that the consequent is inferred to a degree of γ_r, the same con-

[5] Known as *Exceptio probam regulam in casibus not exceptis*. Another interpretation in legal practice is: if an excepting clause makes it impermissible when there is no excepting clause, that it is necessary that it is permissible, which fits perfectly with the semantics of defeaters. The "necessary" term is relaxed by introducing the certainty factor.

[6] Under this doctrine the most specific norm takes precedence.

clusion might also be derived up to a certain degree $\beta_q \leq \gamma_r$ using defeasible premises. There are two inherited sources of uncertainty: either the premises represent vague concepts or they represent a clearly defined concept, but the facts can only be approximately assigned to the concept represented by the premises. Consequently, the reliance on each conclusion depends both on the certainty factor of the rule (representing how strong the premises sustain the conclusion) and also on the membership function which characterizes the premises. Two complementary inference methods may be considered: fuzzy-based, and respectively rough-sets-based. Consequently, the reliance on each conclusion depends on both the certainty factor of the rule (representing how strong the premises sustain the conclusion) and the membership function characterizing the premises.

Fuzzy Inference. Using the weakest link principle for deductive arguments [10], the conclusion q_0 is as good as the weakest premise, given by $min(\beta_1, ..., \beta_k)$, where β_i is the fuzzy membership. Additionally, the strength of the consequent is also influenced by the certainty factor cf of the inferencing rule, with $\beta_0 = min(\beta_i, \gamma), i \in [1..k]$ (in the fuzzy approach) leading to the following rule.

$$q_0[\beta_0] \xleftarrow{\gamma} \bigwedge_{i \in [1..k]} q_i[\beta_i]$$

Rough Inference. Two techniques are suitable here: the approximation of similarity [11] and the rough membership concept [12]. The first case considers that it would be correct to reason with the neighbors of perceived values, rather than a crisp probability value. The conclusion q_1 would inherit the inaccuracy of the perceived premises and their associated tolerance spaces. In this situation, one must assume that every attribute in table 3 has a lower and upper approximation. The approach takes into account the inherent perceptual or contextual limitations, in the latter case two intervals being defined.

In the second case two intervals are defined. Under the double interval notation $\langle UAI : LAI \rangle$ [12], $UAI = [u^s, u^e]$ represents the interval where the fact is defeasibly derived, and $LAI = [l^s, l^e]$ the interval where the fact is certainly true. With $u_0^s = max(u_i^s)$, $u_0^e = min(u_i^e)$, $l_0^s = max(l_i^s)$, $u_0^e = min(u_i^e)$, $i \in [1, k]$ we have the following rough rule.

$$q_0[u_0^s, u_0^e] : [l_0^s, l_0^e] \xleftarrow{\gamma} \bigwedge_{i \in [1..k]} q_k[u_k^s, u_k^e] : [l_k^s, l_k^e]$$

The certainty factor within the UAI is computed according to a rough membership function which must meet three constraints: complementarity, nonmonotonicy, border conditions [12]. The function is designed by the mediator taking in consideration statistical data and some sense of symmetry.

4.2 Level of acceptance

The next step consists in determining the minimum degree of certainty assigned to a defeasible premise within the UAI in order to act as a valid antecedent when it fires a rule. For each antecendent a supporting the consequent q, we use use a rough membership coefficient derived from the initial dataset, according to the formula: $\beta^a_{min}(q) = support(a)/support(a,q)$. For instance, in table 3, $\beta^{supplementary\_charge}_{min}(refund) = (8+4)/(8+4+20) = 0.375$ and for $\beta^{contractual\_clause}_{min}(refund) = 4/(4+20) = 0.17$. This parameter acts as a guideline in the process of accepting a fact as realiable for the current situation. The reason behind the formula relies on the intuition that the attributes which highly influence the outcome must meet a similar level of certainty to be accepted in the argumentation process. Some adjustments of the parameter, in the spirit of tolerance spaces in [11] may be useful, by considering the $\beta^a_{min}(outcome) - \varepsilon$, where ε depends both on the relience or importance given to dataset in the current dispute and on the phase of the current dispute. In the former case, high reliance implies $\varepsilon \longrightarrow 0$, and in the latter one, $\varepsilon < 0$ should be used in the early stages, while $\varepsilon > 0$ in the advanced phases of the dispute[7]. The mediator having designed a rough membership function for each attribute, it can extract the certainty factor β_q for that fact q. If $\beta_q \geq \beta^q_{min}(oucome) - \varepsilon$, the premise will be accepted in the argumentation process.

4.3 Accrual of arguments

The same conclusion q can be sustained by several pro and counter arguments with different degree of reliance $\beta_q \geq \beta^q_{min}(oucome) - \varepsilon$. In our approach the accrual of arguments does not hold. The types of defeaters are treated differently to achieve different patterns of defeasible reasoning [10]. The strongest undercutting defeater contributes to the decreasing of the certainty factor and if the remained strength of the conclusion overwhelms the most powerful rebuttal defeater, the respective conclusion is derived. Formally:

$$\beta_q = \begin{cases} max(\beta_{q_i}) - max(\beta_{\sim q_j}) & if\ max(\beta_{q_i}) - max(\beta_{\sim q_j}) > max(\beta_{\sim q_k}) \\ 0 & \text{otherwise} \end{cases}$$

4.4 Defeasible derivation of a consequent.

Having defeasible rules and accepted valid premises with a level of certainty, the next stept consists in inferring the possible consequences. Next we present the

[7] It is possible to define thresholds to decide, during dispute resolution phases whether a given claim is fulfilled or not. The certainty factor of the conclusion must meet the level of confidence accepted for each dispute phase: scintilla of evidence in dispute commencement (20%), preponderence of evidence in discovery phase (50%), clear and convincing evidence (75%) in arbitration phase, and beyond resonable doubts in post-trial or appeal(95%). These thresholds correspond to credulous, caution, or respectevly skeptikal attitudes as defined in [13].

derivation formula of a consequent according to the argumentation semantics of the defeasible logic. A conclusion in a defeasible logic theory is a tagged literal which can have the following forms: i) $+\Delta q :\Leftrightarrow q$ is definitely provable using only strict facts and rules (figure 3); ii) $-\Delta q \Leftrightarrow q$ is not definitely provable; iii) $+\partial q :\Leftrightarrow q$ is defeasible provable (figure 4); iv) $-\partial q \Leftrightarrow q$ is not defeasible provable. A conclusion q is strictly provable (figure 3) if (1) q is a strict fact valid or (2) there exists a strict rule r with conclusion q which rule (2.1) have all its antecedents a valid and (2.2) there is no a strict negated rule ns, attacking the rule r.

$+\Delta$:
If $P(i+1) = +\Delta q$ then
(1) $\exists q(\beta) \in F$ and $\beta = 1$ or
(2) $\exists r \in R_s[q]$ such as
(2.1)$\forall a \in A(r) + \Delta a \in P(1..i)$
(2.2) $\nexists ns \in R_{ns}[r]$

Fig. 3. Definite proof for the consequent q.

The sentence q is defeasibly provable[8] (figure 4) if (1) it is strictly provable, or (2) there is a valid support for q either (2.1) it is a defeasible valid fact, or (2.2) there exists a rule with all premises valid sustaining that conclusion q and it is not defeated by (2.3) a negated rule with a stronger certainty factor, or (2.4) by an undercutting defeater def where (2.4.1) the defeater has an antecedent a which cannot be derived, or (2.4.2) there exists a negated defeater stronger than def, and (2.5) for all rebuttal defeaters d either (2.5.1) there is a negated rule which defeats d or (2.5.2) the support for conclusion q after it is attacked by the undercutter defeaters remains stronger than all the valid rebuttal defeaters. The non strict order relation in (2.3), (2.4.2), and (2.5.2) does not provide a skeptical reasoning mechanism, meaning that both of q and $\sim q$ may be derived when they have equal support[9].

5 Discussion and Related Work

The essential advantage of our approach compared to the existing ones for deriving defeasible theories from data [3, 14] is that we do not assume that the

[8] The answer to a defeaseable query is based on premises situated in the boundary region, similar to the concept of approximation queries in [11].

[9] In some cases the law gives no straight answer and consequently judges can legitimately decide either way. Allowing ambiguity propagation increases the number of inferred conclusions, which can be useful in the argumentation process. ODR systems oriented towards solution rather than finding the degree of guilt can benefit from this ambiguity propagation.

$+\partial$:
If $P(i+1) = +\partial q$ then
(1) $+\Delta q \in P(1..i)$ or
(2) q is supported
(2.1) $\exists q(\beta_q) \in F$ and $\beta^q_{min} < \beta_q < 1$ or
(2.2) $\exists r(\gamma_r) \in R_{sup}[q]$, $\forall a \in A(r)$ such as $+\partial a \in P(1..i)$, $\beta_a \geq \beta^a_{min}$, and not defeated
(2.3) $\forall nd(\gamma_{nd}) \in R_{nd}[r] \cup R_{ns}[r], \gamma_r \geq \gamma_{nd}$ and
(2.4) $\forall def(\gamma_{def}) \in R_{def}[q]$ or
(2.4.1) $\exists a \in A(def) - \partial a$ or
(2.4.2) $\exists ndef(\gamma_{ndef}) \in R_{ndef}[def],\ \gamma_{ndef} \geq \gamma_{def}$ and
(2.5) $\forall d(\gamma_d) \in R_{sup}[\sim q]$ with
$\forall a(\beta_a) \in A(d)$, $+\partial a$ and $\beta_a \geq \beta^a_{min}$ either
(2.5.1) $\exists nnd(\gamma_{nnd}) \in R_{nd}[d] \cup R_{ns}[d], \gamma_{nnd} > \gamma d$, or
(2.5.2) $\gamma_r - \gamma_{def} \geq \gamma_d$

Fig. 4. Defeasible derivation of consequence q.

available information is consistent. Another fundamental difference regards the reasoning pattern. The algorithm HeRO in [3] is based on a conservative mode of operation that does not draw any conclusion in case of doubt. This seems to be an unacceptable constraint, as the practice in law has already proved, in our approach we relax this skeptical resoning mechanism.

The Apriori algorithm was used [14] to generate association rules in order to facilitate the discovery of defeasible rules. Association rules are used to suggest hypotheses. These candidate defeasible rules are then reduced by applying support, confidence and interest metrics. In the rough set approach the irrelvant defeasible rules candidates are not even computed, because they are derived from reducts which contain only the important attributes. We advocate an important advantage of our approach, namely, the framework is adapted to the limitations of practical scenarios[10]. Thus, the rough sets approach is extremly suitable for those practical scenario where the information is gradually revealed and where in the first phases the indiscernability is present.

To the best of our knowledge this is the first attempt to combine rough set theory with defeasible reasoning aiming to provide a framework that covers both aspects of the law: case based reasoning and legal syllogism. Given the current demand for ODR technologies, the potential of such an argumentation framework is extremely promising. Our future work regards the enrichement of the logical framework with explanation capabilities of the outcome, as a need for the trustworthiness and practical usability as a dispute resolution system. However, the variant of the defeasible logic proposed here offers a rich knowledge representation formalism and a clearly interpreted theory, with the adequate argumentative semantics for legal reasoning.

[10] These include both medical diagnosis and legal reasoning where the subjects may not be used to obtain initially all kind of information with the only aim that a decision support system to optimise its outcome.

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