Predicting Court Decisions for Alimony: Avoiding Extra-legal Factors in Decision made by Judges and Not Understandable AI Models

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Abstract

The advent of machine learning techniques has made it possible to obtain predictive systems that have overturned traditional legal practices. However, rather than leading to systems seeking to replace humans, the search for the determinants in a court decision makes it possible to give a better understanding of the decision mechanisms carried out by the judge. By using a large amount of court decisions in matters of divorce produced by French jurisdictions and by looking at the variables that allow to allocate an alimony or not, and to define its amount, we seek to identify if there may be extra-legal factors in the decisions taken by the judges. From this perspective, we present an explainable AI model designed in this purpose by combining a classification with random forest and a regression model, as a complementary tool to existing decision-making scales or guidelines created by practitioners.

1. Introduction

Machine learning —the study of algorithms that allow computer programs to automatically improve through experience (Mitchell, 1997)— has brought artificial intelligence to the forefront in the past decade, in particular thanks to new techniques such as deep learning (Sejnowski, 2018). Since then, classification or clustering techniques have really improved. Effective AI-based applications —or "classifiers"— have been able to be realized in very diverse fields, whether for pattern recognition or decision support systems, and they are able to perform complex tasks in place of humans.

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Machine learning algorithms are used in finance, medicine, and criminal justice, and therefore they can have a deep impact on society. With the recent success of AI applications in the private and public domain, legal professionals are now interested in artificial intelligence, especially since many startups disrupt the legal market space by seeking to benefit of these new AI techniques (Bex et al., 2017).

However, the arrival of these new techniques has brought a number of ethical issues. Firstly, machine learning and data mining techniques are capable of exploiting personal and legal data that are more and more easily accessible on the Internet, leading to questions about privacy preserving, or even attacks on democracy (Wylie, 2019). Secondly, artificial intelligence programs reason in a simplistic way, but the real world is complex, especially in the legal field which leaves a certain part to the human interpretation of the law and characterization of the fact. A machine learning program has great difficulty in dealing with the unexpected events that happen in the real world. Intelligent system algorithms are black boxes that are impossible to understand, they are unregulated and difficult to question in the case of the presence of bias, and in some cases they amplify inequalities (O'Neil, 2016). Thirdly, when a classifier learns about data collected on past situations, it performs statistical deductions and transform correlations between variables into implication relationships. This can lead to problems with dramatic consequences such as gender bias or racial discrimination (Angwin et al., 2016).

We present in this paper a method to predict the spouses' alimony after a divorce in France. To do this, we have a corpus of first instance court decisions (formerly known in French as "tribunal de grande instance," now "tribunal judiciaire") which have already been subject to traditional analysis (manual data entry, statistical and econometric analyses). This allows us, by working on the same corpus, to test the reliability of the results obtained and to exceed the methodological limits encountered. This paper is organized as follows: Section 2 provides information on the interest of the various stakeholders in advancing the knowledge of the determinants of court decisions. Section 3 presents a state of the art, not only on the technical progress made in the field of machine learning and law and predictive judicial

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analytics, but also on the ethical difficulties identified. We present our project on the study of the knowledge extracted from jurisdictional productions in Section 4, how this study relates to the analyses on the determinants of the economic consequences of a divorce, and how this knowledge can be used for the design of decision support tools. An alimony prediction model is proposed in Section 5, followed by the results of its application to the available data in Section 6. We discuss the results obtained in Section 7.

2. Motivations

The study we propose in this paper focuses on the prediction of the alimony after a divorce. An *alimony*, also known as *spousal support*, is defined as the "transfer of income between spouses intended mainly to reduce inequality in living standards following a divorce" (Bourreau-Dubois & Doriat-Duban, 2017). Our objective however is not only to produce a simple predictive model. This work is motivated by a differentiated contribution that we can have for the different types of actors concerned by the subject. The various stakeholders have indeed every interest in advancing in the knowledge of the determinants of court decisions, but their motivations differ according to their position.

First, for the litigants –whose positions are known through interviews with their lawyers– what is most important is to have an idea of what they can expect from the court decision. Applied to the economic consequences of a divorce, it is a question of whether they can expect to receive (or pay) an alimony and how much it will be. This information not only makes it possible to plan for the future but also to base more global negotiations on the whole of the consequences of the divorce. However, by providing a list of non-exhaustive, non-prioritized criteria, and sometimes by referring to facts that are difficult to establish, the drafting of the law makes alimony one of the elements of the divorce decision the most difficult to anticipate.

Second, for the lawyers, the motivation relates to the need to respond to the predictability concerns of their clients, and thus to show that they have mastered the subject. They must also establish a judicial strategy to defend in the best interests of divergent interests, either by helping the divorcees to reach an agreement, or by making a legal claim. In either case, it is important to have objective criteria by which to provide guidance to their clients on what they can expect from a court decision. However, they know that the hazard is important too. They use therefore increasingly decision-making tools such as scales or guidelines created by practitioners, predictive judicial analytics tools (Chen, 2019) put on the market by private companies (De Jong, 2019), or databases which provide them with quantified case law.

Third, for the judges, there is no consensus: they are divided on the advisability of using decision support tools, while recognizing that fixing alimony is difficult. They are generally very attached to their appraisal and they consider these tools to be optional, but they still use the decision-support tools that are the scales created by practitioners (Sayn et al., 2019). The use of predictive judicial analytics tools, which relate to the analysis of large amount of court decisions, is seen as potentially affecting their freedom to decide, by allowing judge profiling (prohibited by French law). However, the desire to produce comparable decisions for comparable clients' cases is very present, especially for judges who assume managerial responsibilities within the jurisdiction: they must pay great attention to the importance of the regularity of the decisions rendered in their jurisdiction. For jurisdictional organizations, predictability is also considered as the means to favor agreements and unclog the courts.

Fourth, from the research point of view, the production of knowledge is an end in itself. Knowing the determinants of court decisions is part of a realistic approach to the law, in which judges have a prominent role in the application of general and abstract rules to particular situations. It is a question of better knowing the decision-making mechanisms and of identifying not only how the legal criteria for decision are used but also to know if other criteria interfere in the decision of justice, i.e., bias or extra-legal factors. However, traditional analyses are very cumbersome to implement (manual entry) and not always sufficiently efficient for the identification of the determinants of decisions (statistical and econometric analyses). The use of AI is considered here as a way to overcome this methodological bottleneck. For researchers in computer science and mathematics, the objective is different but convergent: to be able to develop new predictive models. In this project, collaboration between disciplines is of course essential.

3. Related Work

Intelligent algorithms are applied in the legal field from the beginnings of artificial intelligence with the use of expert systems in the late 1980s (Bench-Capon et al., 2012). When machine learning techniques have been used, it was mainly the methods giving understandable models that have been favored, such as rule-based approaches or dictionary-based models. Decision trees (Quinlan, 1986) and random forests (Breiman, 2001), as well as techniques derived from them (e.g., extremely randomized trees (Geurts et al., 2006)), have been widely used for predictive judicial analytics purposes (Katz et al., 2014). More recently, the use of Natural Language Processing techniques (such as N-gram features obtained with a Bag-of-Words model) combined with statistical approaches (e.g., SVM (Vapnik, 1998)) have also shown very good results in predicting court decisions (Ale-

tras et al., 2016). Deep Neural Networks have also been applied in legal analytics in recent years, replacing more traditional techniques that required expensive manual processing and only achieved poor performance (O'Neill et al., 2017). The WORD2VEC model (Mikolov et al., 2013), with the skip-gram and Continuous Bag-of-Words (CBOW) algorithms, is capable of finding semantic similarities on the basis of the co-occurrence of terms in large corpora of documents. By using a legal corpora from various public legal sources for training such a model, it is now possible to use a Law2Vec model to provide the semantics associated to legal words in English (Chalkidis & Kampas, 2019).

There are many machine learning techniques used in the law, but what do people really want? In addition to greater efficiency in the legal process, which is a stressful but also costly and time-consuming process, the answer to this question depends on the type of stakeholder (Muhlenbach & Sayn, 2019). The use of machine learning is also motivated by the fact that a machine is supposed to not be sensitive to the same extra-legal factors as a human being, as can be judges who are more or less lenient in their decisions depending on the time of day and what they ate (Danziger et al., 2011). In addition, judges are expected to apply the law in the same way, regardless of their personal value scales, sensitivities, or political orientation (Cohen & Yang, 2019). Nevertheless, inter-judge disparities in predictions are high, so much so that it was possible to predict the outcome of a trial with a fairly good success score by taking into account as variable only the surname of the judges that try the case (Medvedeva et al., 2020). Thanks to sentencing guidelines, it is fortunately possible to reduce the disparities between judges (Bourreau-Dubois et al., 2020).

Human judge decisions are not pure: they can be biased, whether the judges are aware or not of these biases and extra-legal factors. However, since machine learning algorithms are based on court decisions that contain biases, it is to be expected that the classification models they produce will also be tainted with these same biases. Scattered within a few connection weights between neurons lost in a deep neural network or associated with a variable that will play a role in removing the model from the legal framework, such a bias can be extremely difficult to find, which makes the source of the problem difficult to identify, and preventing any rational and justified explanation in a court (Barocas & Selbst, 2016). Different strategies have been studied to combat these biases. On the data side, to counter the problem of unbalanced data which tends to reduce the chances of people from minorities in decision-making problems (e.g., remission of sentences, access to consumer credit, selection of an application for a position), studies suggest collecting more data for increasing the sample sizes of these minorities (Chen et al., 2018). On the learning algorithm side, traditional methods have been adapted to deal with these

biases, such as modifying Naive Bayes classifier in order to perform discrimination-aware classification (Calders & Verwer, 2010). In addition, work has been specifically devoted to neutralizing learning biases that pose ethical problems, for example "race neutral" predictive modeling of decisions on pre-trial release and paroling (Lum & Johndrow, 2016; Johndrow & Lum, 2019). Finally, even for models known to be considered as black boxes such as deep neural networks, work has been done to place around them a "glass box" by mapping moral values into explicit verifiable norms that constrain the inputs and outputs, so that these if they remain in the box, it is guaranteed that the system adheres to the value (Tubella et al., 2019).

We can say that, in general, there has been a clear increase in work in the field that has addressed the societal repercussions that machine learning models could have. Many works are no longer just focussing on the prediction accuracy, but also on fairness and equality before the law, on transparency and accountability, and on informational privacy and freedom of expression (Scantamburlo et al., 2018). It must be said that these problems have generated strong reactions, both from civil societies and associations, but also from nations. Regarding this concern for ethical issues related to the use of artificial intelligence and machine learning, we can mention in particular the drafting of the Asilomar AI principles1 in the USA, the Montréal Declaration for a responsible development of Artificial Intelligence² in Canada, the Villani Report "For a meaningful Artificial Intelligence" in France, or the Ethical charter on the use of Artificial Intelligence in judicial systems and their environment⁴ in the EU.

4. Study of the use of knowledge based on jurisdictional productions for the design of decision support tools

The study relates to the alimony prediction in France. This specific focus allows to understand the court decisions and see how they are conceived on this particular question.

Following a partnership with the French Ministry of Justice, thousands of court decisions dating from the year 2013 covering dozens of first instance courts were collected and analyzed. At the time of the study, in France, there were 173 trial courts of this type (i.e., one or more per French department). These court decisions have therefore already been the subject of a first analysis: the researchers developed a data entry grid based on the reading of part of them and then proceeded to the data entry from one-to-one reading of

https://futureoflife.org/ai-principles/

²https://tinyurl.com/y3ban2eq

https://www.aiforhumanity.fr/en/

⁴https://tinyurl.com/y9tknlba

court decisions. The database created in this way was finally subjected to statistical and econometric analyzes. With this first study, the researchers conclude, for example, that the duration of the marriage or the incomes of the spouses are the determining factors. In the calculators found online to assess the amount of an alimony –in particular for the different states of the United States or the different provinces of Canada–, we find equivalent results: the marriage length in years and the gross incomes of the two spouses are the data always requested.

The study was not conducted with a purely predictive objective. The idea behind this work was rather to report on the processes followed by the judges to make their decisions, and more particularly concerning the following points:

- find the determinants allowing to indicate that a litigant (a former spouse) is eligible or not for the alimony;
- find the determinants used to calculate the amount of this alimony;
- analyze the determinants in order to see if there are hidden extra-legal factors among them.

This study indeed makes it possible to identify if there are extra-legal factors that must be integrated into the model to understand the way in which judges make their decisions (e.g., if there is an effect of the judge, if there is an effect of the lawyer, or even an effect of the court). As the first instance courts are associated with a given jurisdiction, therefore with a specific geographical area of France, it is interesting to see if there are differences between the different seats of the courts.

5. Alimony Prediction Model

Consider a corpus of first instance divorce court decisions codified in a database, representing the legal production carried out at national level in France, we conduct a predictive analysis which aims to:

- Step 1: predict the alimony eligibility and acceptance by the court;
- Step 2: predict the alimony amount set by the court;
- Step 3: adjust the alimony amount from step 2 by the outcome from step 1.

For the learning phase, the model is trained with court decisions in a supervised way by using two submodels: a classification model in step 1, and a regression model in step 2. We predict the adjusted alimony amount by considering both its acceptance probability and the amount:

$$\widehat{y}_{alimony} = \widehat{y}_C \times \widehat{y}_R$$

where $\hat{y}_{alimony}$ is the adjusted alimony amount and \hat{y}_C , \hat{y}_R are respectively the predicted variable of the classification and the regression model.

Note that \hat{y}_C is recoded to 0 for absence of alimony and 1 for acceptance of alimony. This configuration makes it possible to cross the variables which relate to the alimony eligibility and those on the alimony amount. Although regression hardly gives exactly zero as the outcome, observed alimony amount could be zero while the divorcing spouses are not eligible to the alimony for example. Those cases disturb the regression as the linear relationship assumption is not satisfied. By splitting the alimony prediction model into two independent submodels, we can solve this problem.

6. Experiments

6.1. Dataset

We validate our model using a database collected previously as part of a collaboration with the Ministry of Justice. The database, made up of 5,453 divorce decisions, contains 3,203 cases for which the question of granting an alimony arose and in only 2,678 of them ultimately an alimony was approved by the court. It is therefore possible to calculate a success rate and to answer, by comparing the two types of cases, a predictive question of the court knowing the divorcing spouses situation and their alimony request.

The proposals for the alimony amount made by the divorcing spouses, if mentioned in the decisions –which is not always the case– can be expressed either in terms of monthly payment or in terms of capital (Belmokhtar & Mansuy, 2016). We only have 280 cases (8%) with a court decision on the form of monthly payment, and we decide to not include those atypical cases in our model.

Moreover, the database consists of two very distinct situation, after deletion of the unusable cases. The first situation concerns the 1,524 cases where the parties have agreed, here the offer is equal to the demand and this amount is approved in more than 99% of the cases by the judge. This systematic approval explains the almost perfect estimate of the amount of alimony set by the judge. The second situation concerns the 1,257 cases where the parties did not agree neither on the amount nor the principle of the alimony. It is thus only on this small subsample that the question of the estimation of the alimony from the court decision is really relevant.

6.2. Feature Selection

The prospect that the "Loi pour une République numérique" ("Law for a Digital Republic," known as the Lemaire Law, 2016) opens in the field of law, namely the free access of all French court decisions digitized in the near future, would facilitate the application of machine learning models.

Table 1. List of the most important features in classification whether to grant alimony or not using Gini importance

VARIABLES	Gini
ACTIVITY STATUS OF THE WIFE	19.9
ACTIVITY STATUS THE HUSBAND	15.6
SALARY OF THE HUSBAND	30.5
RETIREMENT PENSIONS OF THE HUSBAND	13.4
SALARY OF THE WIFE	26.1
OTHER INCOME OF THE WIFE	10.6
NB OF CHILDREN FROM THE COUPLE	16.2
NB OF ADULT CHILDREN OF THE COUPLE	13.7
COMMON LIFE DURING MARRIAGE	21.4
TEMPORARY SUPPORT PAYMENTS	25.0
TEMPORARY ALLOCATION OF DOMICILE	10.7
CAPITAL PAID AT ONCE REQUESTED	33.7
TYPE OF CAPITAL IN CASH REQUESTED	16.2
TYPE OF CAPITAL IN CASH OFFERED	18.5
SEAT OF FIRST INSTANCE COURT	107.1

However, the court decision annotation is an expensive and time-consuming process. Therefore, searching for important determinants makes the model explainable and reduces the cost of data labeling for new court decisions. We perform a feature selection for each of our submodels.

6.2.1. CLASSIFICATION

To identify the determinants, we use the most common algorithm with tree-based models: the Gini importance (Breiman et al., 1984). This criterium counts the number of times a feature is used to split a node, weighted by the number of observations in the node. The 15 most important variables presented in Table 1 lead to the following observations: (1) The professional situation of the divorcing spouses is determinant as both the activity status and the income are important. (2) The appearance of the variable "Seat of First Instance Court" is surprising and should not take place because the law should be the same throughout the French territory.

The goal of our work is to build an ethical, unbiased model, without extra-legal factors. Despite its importance, we decide to not use the variable "Seat of First Instance Court." In order to overcome this problem, we use a Random Forest classification with only the 14 variables left. After tuning our predicting model, we obtain an accuracy rate of 99.89% and an AUC of 0.999. This almost perfect rate shows that using extra-legal factors like "Seat of First Instance Court" is unnecessary.

6.2.2. REGRESSION

We use a stepwise forward selection to identify significant features. We report a multiple R-squared of 0.6619 and an adjusted R-squared of 0.6579 with an Ordinary Least

Squares regression (Goldberger, 1964). Results in Table 2 lead to following observations: (1) The proposals for the alimony amount made by the divorcing spouses (offered and requested) are decisive as far as the judge must decide infra petita. We can then see that supply and demand almost perfectly explain the amount of alimony fixed. We could therefore conclude that it is almost enough to know the proposals to determine the amount withheld by the court. (2) Interim measures are temporary measures taken by the judge to officer the conjugal and family life of the divorcing spouses during the process of divorce. They are set at the time of the conciliation hearing.⁵ They take effect from this date and end at the time of divorce. These interim measures are good predictors of the alimony amount, in particular the temporary pension offered during the non-conciliation order. Indeed, it is common knowledge that some judges fix an alimony amount equal to a multiple of the amount of temporary pension.

Table 2. List of the most important features in regression using forward stepwise

VARIABLES	ESTIMATE
INTERCEPT	8403.15
CAPITAL AT ONCE REQUESTED	0.33
CAPITAL AT ONCE OFFERED	0.79
CAPITAL AT ONCE IN A JOINT REQUEST	0.88
CAPITAL OVER TIME OFFERED	0.48
CAPITAL OVER TIME IN A JOINT REQUEST	0.80
CAPITAL OVER TIME REQUESTED	-0.56
MONTHS OF CAPITAL OVER TIME REQUESTED	353.42
PENSION OFFERED	-88.72
PENSION REQUESTED	40.80
TEMPORARY PENSION OFFERED	1.37
SALARY OF THE WIFE	-7.86

From the Table 2, we can easily calculate the amount of \hat{y}_R from the following equation:

$$\begin{array}{cccc} & 0.33 \times & \text{Capital at once requested} \\ + & 0.79 \times & \text{Capital at once offered} \\ + & & \dots \\ \\ \widehat{y}_R = & + & 40.80 \times & \text{Pension requested} \\ + & 1.37 \times & \text{Temporary pension offered} \\ - & 7.86 \times & \text{Monthly salary of the wife} \\ + & 8403.15 \end{array}$$

With an intercept whose value is very different from zero,

⁵The programming and justice reform law 2018-2022 of March 23, 2019 modified the divorce procedure and notably abolished the previously compulsory conciliation hearing for contentious divorce (art. 22). This development, which will take effect on September 1, 2020, does not exclude the possibility of fixing provisional measures during a first hearing.

it is very difficult to get an null estimate of \widehat{y}_R (corresponding to a non-allocation of an alimony by the judge). This motivates the interest of having made a combination model between a classification method (giving a value of 1 or 0) and a regression method.

The Figure 1 presents the predicted value for the alimony \widehat{y}_R as a function of the set of the variables selected for the model (Table 2). The figure is however not very representative of the quality of the model: the first component of the principal component analysis made on the dataset explains only 20% of the variance in the data (all the 11 continuous variables kept for the regression model are necessary for the alimony amount prediction, but these variables are not correlated with each other).

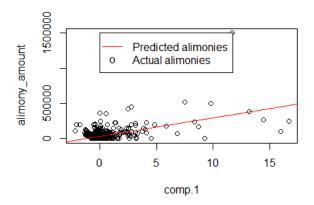


Figure 1. Multiple linear regression prediction of the alimony as a function of the set of variables selected for the model (1st component of the PCA).

6.3. Performance Comparison

Our model performs best by fusing a Random Forest (RF) classification algorithms with an Ordinary least squares (OLS) regression or a Quantile regression. OLS regression models the effect of explanatory variables on the mean value of predicted variable. As the mean is more affected by outliers and other extreme data present in our database, we also use the quantile regression (Koenker, 2005) which estimates the conditional median of the predicted variable.

In order to measure the relevance of our predictive model, we have calculated the absolute value of the difference between the actual value and predicted value. We report the results distributions, called absolute errors, for each of the two regressions by themselves and by application of our model in Table 3.

The prediction absolute errors presented in Table 3 lead to

Table 3. Absolute errors in prediction (in thousands of euros)

Model	MEAN	MEDIAN	σ	R^2
OLS REG.	21.46	10.64	35.93	0.66
QUANTILE REG.	19.73	9.04	40.93	0.62
$RF \times OLS$ Reg.	16.46	3.95	35.59	0.70
$RF \times Q$ uantile Reg.	15.95	3.43	32.01	0.65

the following observations: (1) Quantile regression gives less errors. (2) Our alimony prediction model outperforms each regression. (3) A lower R-squared is not inherently bad.

7. Analysis and Discussion

Another possibility for selecting the variables is based on the statement of the Civil Code. The rules relating to the alimony are provided on articles 270 to 281 of the Civil Code. These provisions mention in particular its calculation criteria, its terms of payment or revision of its amount, or even the rules applicable in certain specific situations such as the death of the debtor. We can cite the two most important.

Article 270: "One of the spouses may be required to pay the other a benefit intended to compensate, as far as possible, for the disparity that the breakdown of marriage creates in the respective living conditions. (...) However, the judge may refuse to grant such a service if equity requires it, either in consideration of the criteria provided for in article 271, or when the divorce is pronounced at the exclusive wrongs of the spouse who requests the benefit of this service, in view of the specific circumstances of the breakdown."

Article 271: "The alimony is fixed according to the needs of the spouse to whom it is paid and the resources of the other, taking into account the situation at the time of the divorce and its development in the future predictable. To this end, the judge takes into consideration in particular:

- the duration of the marriage;
- the age and state of health of the spouses;
- their professional qualification and situation;
- the consequences of the professional choices made by one of the spouses during the common life for the education of the children and the time that it will still be necessary to devote to it or to favor the career of his spouse to the detriment of his own;
- the estimated or foreseeable patrimony of the spouses, both in capital and in income, after the liquidation of the matrimonial regime;

- their existing and foreseeable rights;
- their respective retirement pensions situation, having estimated, as far as possible, the reduction in pension rights that may have been caused, for the spouse claiming the compensatory allowance, by the circumstances referred to in the sixth paragraph."

Clearly, our feature selection technique do not give all of those legals determinants the same importance especially when the reconstruction of these indicators requires mobilizing dozens of information provided in the decisions. It is not always easy to measure for example: "the disparity that the breakdown of marriage creates in the respective living conditions." We prioritize the statistical significance in our model in order to provide an accurate prediction. Therefore, among those legal determinants, our classification managed to discover the duration of the marriage, the spouses' professional situation, their incomes, and the husband's retirement pensions. Meanwhile, our regression only takes into account the salary of the wife but depends a lot on the supply and demand for alimony from both parties. It is not surprising that the amount fixed by the judge reflects the requests of the parties, the judge having the general obligation to rule in this context. The results obtained show that the magistrates respect this procedural rule which, in the end, prevails over the legal criteria of decisions. We can therefore suggest that it is upstream, at the stage of developing requests, that these legal criteria can play. Moreover, except the salary of the wife, variables used for classification are not reused for regression in our model.

In term of performance, a median absolute error of only €3,432.98 and a variability of the alimony explained up to 70% clearly show the superior quality of our model compared to a regression. However, our model suffers from a slight underestimation bias because the predicted alimony mean are respectively €28,826.45 for the OLS regression and €24,142.24 for the Quantile regression compared to the average alimony in our database of €33,653.89. We note that the difference between the average alimony in our database of €33,653.89 and its median of €15,000.00 is strongly determined by extreme deviations.

Despite the globally satisfying quality of prediction, we cannot fully trust a tool which, on average, offers a prediction generating an error that exceeds half of the actual alimony amount.

8. Conclusion and Further Work

The recent increase in the efficiency of machine learning algorithms has allowed the arrival of new tools based on artificial intelligence. Since then, new companies exploiting these tools and technologies have appeared all over the world on the legal market space. Even if it seems to be emerging that AI will not replace lawyers, it is likely that lawyers using AI-based tools will replace traditional lawyers.

The work presented in this paper does not seek to produce an AI system capable of making decisions automatically, possibly replacing lawyers. From our perspective, AI is not used to make decisions but to provide information on only part of what constitutes a court decision, relating to the setting of an amount. In this context, the objective is not to design a machine capable of following a reasoning allowing to reach an overall result (a decision) but only to know those of the criteria which determine the amounts retained by the magistrates, in the exercise of their discretion. This allows us to know and understand the ways in which judges use the margin of freedom left to them by the necessary incompleteness of the law. It is above all a question of knowledge, allowing both to show the judicial uncertainty, to explain it and to detect if there is any implicit bias in action. The distinction in the analysis between the legal determinants of the decision and the non-legal determinants pursues this objective. This knowledge can also be a lever for action, by making it possible to offer professionals a decision support tool. The assumption is that such tools would have an effect on practices, as long as they were fairly widely used. However, it is not a question of freezing these practices, not only because decision-making tools can remain optional but also because their mastery by professionals leads to their development. It is therefore not a question of blocking the future from data taken in past decisions, even when the legal and social context is changing, but of giving ourselves the means to steer desirable developments.

In the specific area of the alimony studied here, such an evolution may be desirable, for several reasons. On the one hand, at the stage of the judicial decision (and without prejudging what happens at the stage of the preparation of the requests), it has been shown that the legal criteria supposed to condition the amounts withheld only intervene on the principle of allocation of a service. On the other hand, the logic behind the work before the referral to the judge remains poorly understood, as shown by the tools already used by practitioners, both numerous and very different from each other. Questions remain unanswered: what are we trying to compensate for? are legally legitimate claims for benefits still being made? how do the parties and their lawyers determine the requests they make? It is therefore not necessarily appropriate to deduce from the only data presented here an operational scale, even if the data were sufficient. Moreover, this data can be invaluable in constructing a scale which effectively helps the magistrates and the parties to fix comparable amounts in comparable situations.

In the continuation of our work, we plan to develop systems

for automatic analysis of raw texts of court decisions in order to directly detect the values of interest in the text (with NLP and text mining techniques), avoiding the long and tedious phase of manual document analysis. A useful model must represent suitably the behavior of what it is supposed to model. It is therefore necessary to carry out a regular update by feeding the model with new examples of court decisions, reflecting the decision-making mechanisms of judges and the way they have to make their decisions according to the evolution of society and changes in the law. For example, same-sex marriage in France has been legal since 18 May 2013. So there are now also possibilities for same-sex divorce, thus leading to cases of determination of alimony hitherto not encountered.

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