Application of Machine Learning Metrics for Dynamic E-justice Processes

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***Abstract*—Decision support systems (DSS) in law enforcement have a long history. Starting from the late 50s, they have been developed through several architectural approaches. Still, having a proven capability of DSSes to improve legal practice, the real-world application is limited due to multiple issues, including lack of trust, interpretability, validity, scalability, etc. The paper develops a service-based decision support platform for machine learning applications for eGovernance and internal policy modelling and presents a case study of the application of the platform for the case of migration law enforcement. The artificial intelligence core of the platform was built upon a knowledge base, which includes machine learning models and methods. In this work we have developed a method of structuring, analysis of legal data models based on machine learning. In the course of computational experiment, the efficiency of the developed method was proved and the interpretation of the obtained results was performed to provide recommendations for the enhancement of administrative regulation.**

I. Introduction

Decision support systems (DSS) have a long history in the law enforcement [1]. Starting from the late 50s, they have been developed through several architectural approaches. Still, having a proven capability of DSSes to improve legal practice, the real-world application is limited due to multiple issues, including lack of trust, validity, scalability, etc. Since the 1990s, the idea of creating systems to support legal decision-making that do not produce imperative independent reasoning and conclusions has become popular worldwide. The research of intellectual legal systems was focused on the tasks of search and reasoning until the 1990s. Later it began to expand towards multitasking. The digitalization of administrative processes that is currently happening provides prospects for the application of machine learning methods for the data and process analysis [2]. This leads to the possibility of application of text mining, data mining, and process mining methods for an enhanced comprehending of the legal processes and the way they can be optimized. However, there is still an issue of the quality and structure of the data, which prevent us from the efficient application of machine learning methods that require highly structured data. Moreover, laws undergo constant modifications, which demands automatic tracking of the legal practice like application pattern recognition. Artificial intelligence-based systems can automate the process of text mining and process mining to provide structured data and enable the analysis of the law practice.

II. Related works

Over the past 30 years, a large number of legal information systems have been developed:

- with the argumentation function (for example, BankXX [3], LexrideLaw [1], as well as the NAI framework Web application on the SaaS architecture [4]);
- with the prediction function (for example, SPLIT-UP [5], SMILE+IBP [6], VJAP [7]);
- with integration of document, content and knowledge management functions (FLEXICON [8], KONTERM[9], experimental software and hardware system for scientific and practical search and management of multimedia court content based on procedural ontology e-Sentencias [10], EUNOMOS [11], CLIEL [12]).

As a result of the widespread digitalization and the development of e-government, the rationale and development of legal systems for reference purposes have become particularly important. For example, models have been proposed to ensure control and support of the legislative process in a multilingual environment in European countries [13], [14].

In the past 15 years, experiments have been conducted to introduce machine learning and data extraction methods into legal information systems for various purposes [15]–[18] and one interesting recent development of this kind is a CLAUDETTE system [19]. Over the past few years, experiments have emerged to organize information legal systems on the basis of big data [20], [21].

The work on the application of artificial intelligence method to analyze law practice has just started, so we don't have many reference implementations [22], [23]. They are mainly in line with the dogmatic (formal-legal) method, while there are some interdisciplinary projects especially in the info-communicative facets of law [24]. It is necessary to mention that these research works are not based on the most modern accomplishments in information technologies [25].

Governments and law makers in different countries have begun to apply the machine learning for the analysis of law practice. This indicates a rising interest to the machine learning methods in the area of public administration [26]. Governments of larger regions have shown positive experience of application of intelligent data analysis methods and machine learning for

the improvement of administration [27]. For example, for the examination of catering amenities in Chicago [28], for the organization and implementation of fire safety regulation and management in New York [29].

Scientific studies showed the feasibility of text analysis of court decisions in different languages [28]. For example, court decisions on human rights [30] and the research of the German court decision definitions using the specific semantics and language structure of the German language. [31]. However, studies of the Russian law-making can be hardly identified. This is due to the specifics of the language and lack of access to the Russian court decisions.

In Russia, information systems are being developed for forensic analysis, crime detection and investigation. Models for extracting and intellectual analysis are being developed based on extensive court practice data [32], [33].

DSSs have a proven ability to improve legal practice, but their application in real-life situations is limited due to many problems, including lack of trust, validity, scalability, etc. Now, as in early studies, the processing and input of raw data, which are unstructured documents in legal information retrieval systems, requires considerable expert efforts. In addition, these systems are becoming service oriented, completer and more accurate through the use of complex logical, mathematical, statistical and computer methods and facilitate the routine work of lawyers. These systems do not yet provide a high degree of completeness, accuracy and user-friendliness, processing of intellectually complex requests and solving complex problems.

In the UK, Charles Stevens and his colleagues, who created the prototype JAES system, consider it promising to build systems based on legal reasoning on the type of cases, connected to the "whiteboard" template and service-oriented architecture. [34].

Data-driven methods employ large amounts of empirical data processed with statistical machine learning methods to abstract patterns [26]. The need for validity and interpretability is currently recognized as an essential problem to be solved by researchers. Validation of data-driven models often requires lengthy and expensive practical evaluation, using metrics that are intuitive to lawyers and go beyond measures of technical accuracy and include measurements of quality and effectiveness. Implementation and adopting of machine learning methods can be reasonably straightforward. Still, the interpretation of the provided outcomes is sometimes complicated and indistinct due to the black-box nature of machine learning models.

The level of development of e-government is already sufficient to make intellectual analysis and forecasting solutions in the field of law available to the people, researchers and public services. Addressing the weakness of machine learning methods can be done only within a complex sophisticated solution where each step provides traceability and interpretability of the model. Implementation of a pipeline within a technological platform that formalizes each step from a legal text in a natural language to the interpretation of the results will reduce the volume of legal routine and economic costs of legal procedures, and will provide stakeholders with direct access to relevant, concrete and expedient legal knowledge.

III. Objectives

Our research in general aims at development the methods for eGovernance and Policy modeling using artificial intelligence. We propose the architecture that unites legal information systems and services to consider, firstly, variety and variability of computer methods of working with legal data, and secondly, variability in application of methods for solving legal tasks.

This paper develops a service-based decision support platform for a law enforcement and presents a case study of the application of the platform for the migration law enforcement cases.

IV. Methods

This section proposes basic structure and requirements to the proposed approach for Law enforcement decision support systems implementation. The approach includes a pipeline (see Fig. 1) that step by step implements components of a system and brings them together. The holistic approach is based on the tight interconnection of all the stages to support the implementation of a decision support platform.

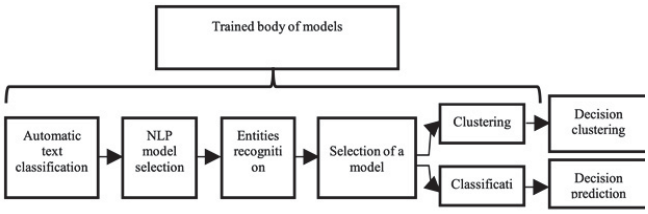

Fig. 1. Decision support pipeline

A. Natural language processing models

The essence of this linguistic specificity of legal tech is commonly expressed by the term "legal language" [35]. In the legal language (and not only Russian) there are special legal terminology (including Latinisms and foreign loanwords), cultural conditionality, style specificity and versatility (including official chancellery style and elliptical constructions) [36].

NLP models vary depending on the structure, content and presentation of data, considering that almost all legal data is weakly structured, its content is determined by the purpose of the legal document and the presentation form - by technical and legal traditions. For example, the NLP model of an administrative offense decree is built by:

- structure - by segmenting the document into introductory, descriptive, motivational and substantive parts
- content - by differentiation of the content of the specified parts (introductory part: name of the judicial body, position and surname of the judge, date and place of consideration of the case, information on the person in respect of whom the case is being conducted, etc.;

- descriptive part: evidence in the case, means of proof, etc.; motivational part: circumstances established during the consideration of the case, evaluation of evidence, qualification of the committed act, etc.;
- operative part: court decision on imposition of administrative penalty, its type and amount or on termination of the case, etc.);
- terms of presentation - on differentiation of the prescribed and free text, identification of quotations, references and word markers, etc.

B. Clustering models

Clustering models ensure reduction of analytical tasks by developing of common options. For example, clustering of the facts of substantive and procedural significance and the results of the consideration of the case of an administrative offense allows developing model scenarios for the court proceedings.

C. Classification models

Classification models provide solutions for predictive problems by selecting scenarios associated with different outcomes. For example, classification of facts of substantive and procedural significance allows predicting the result of a trial: prosecution or termination of a case, choice of the type of administrative punishment and its extent, etc.

D. Decision trees

This approach operates with a series of rules to allow attributing of an entity to a class. The first test should describe the node of the best solution (the main node). A possible result of a test is presented as a branch coming from a node. Every resulting branch either leads to another test (solution node) or to a result (final node). Moving through the solution tree allows selecting a class or a numerical value for each case by selecting one of the branches. Starting from the root, you should move to the next branch until we reach the top. On each node, data is used to determine which branch to choose next.

Classification decision trees are applied to forecast categorical values due to their ability to distribute a value into classes and categories. Regression trees are used to operate with continuous variables.

V. RESULTS

To implement the proposed approach, a platform for model-based decision support was developed. It includes general instrumental solutions and basic methodological procedures for the application of the approach.

Model training block includes a pipeline commonly implemented by data scientists. Still, the pipeline was extended in two aspects. Firstly, it explicitly follows the rule base constructed after the official guidelines, scales, recommendations, etc. to enable referring them within a context of data-driven model application.

The platform currently provides the following functionality:

Private segment

- Service to automate the preparation of appeals to courts
- Forecast of the outcome of the trial
- Search and analysis of model court cases and procedural scenarios
- Expert legal translation

Government segment

- Service for routing of appeals to courts
- Service for automation of preparation of projects of judicial acts, including motivating and operative parts of the judicial act
- Service for generalization and analysis of court practice
- Service for detection and analysis of deviations in judicial practice (deviations from uniform judicial practice, procedural violations, abuse of process participants, crimes against justice, etc.) in order to counteract offences and assess professional performance of judges
- Service for legal monitoring, including qualitative and quantitative assessment of lawmaking and law enforcement
- Service for predicting the validity of regulations under preparation
- Service for law enforcement (image recognition of criminal activity, programming of crime investigation)
- Scientific segment
- Specialized libraries for processing legal texts
- Specialized libraries for legal data processing
- Specialized libraries for legal process processing
- Comparative justice (from different countries)

Educational segment

- Popularization of electronic services among population
- Modules for training students of secondary professional and higher education in legal disciplines (training of legal reasoning, training of legal qualification, training of procedural rules, training of scientific search and justification, etc.).
- Scientific services for the development of legal science
- Classifications of the dynamics of judicial practice
- Interpretation Descriptive models of jurisprudence
- Predictive models of court practice
- Comparative justice of different countries
- Interdisciplinary services
- Formalization of court practice for the following tasks:
- Sociology (hybrid data analysis with social network data)
- Formalizing jurisprudence for domestic policy purposes
- Texts nlp. Text science. Text mining.
- Simulation of complex processes / complex. Process Mining, Complexity
- Behavioral sciences: including modeling the behaviour of people in complex situations with opposite interests (civil law).

VI. CASE STUDY. ADMINISTRATIVE LAW

A. Case study methods

To solve the research task on the intellectual analysis of the judicial practice of application of the article of the Code of Administrative Offences of the Russian Federation at the stage of revision of resolutions (decisions) in cases of administrative offences, the data of the State Automated System of the Russian Federation "Justice" (public resource) were used. The empirical basis in the 8804536 court rulings and decisions in the cases of administrative offences. As a result of queries, full documents of judicial acts were received, which, as a rule, have a large volume, and not all their fields have values (zero values). Fields of documents were filtered out with only significant data left. The data were processed by Apache Spark using Python together with the Jupyter notebook.

The judicial acts in the state information system "Justice" were weakly structured. The basic information necessary for intellectual analysis is contained in them in unstructured form in texts in natural (Russian) language. For this reason, a significant contribution to the quality of the resulting models is made by the developments in the field of natural language text processing. Significant amounts of weakly structured data change the requirements to pre-processing technologies. The necessary data were extracted from the texts of court decisions, on the basis of which the problem of classification was solved [32].

NLP methods

The concept of Term Frequency (TF) and Inverse Document Frequency (TF-IDF) is widely used to compute a weight or importance of a term in a text or a document [37]. As the TF-IDF conception is based on the information entropy and expected mutual information [38] it can be represented the following manner [37]:

Let $D = \{d_1,..,d_m\}$ be a corpus of documents and $T = \{t_1,.., t_k\}$ be a corpus of terms included in D. Then TF-IDF is a matrix n × m, which is built by the following formula:

$$TFIDF(t,d,D) = \frac{n(t_i)}{n(t \mid t \in d_j)} \times \log \frac{m}{|\{d_j \in D \mid t_i \in d_j\}|} \quad (1)$$

where $n(t_i)$ – is the frequency of the term ti in the document d_j [38]. In our study we TF-IDF to produce n-grams.

Correlation analysis

The correlation matrix was calculated using the Pearson correlation coefficient. By the example of the law on migration, a correlative analysis of these court decisions was carried out. The following parameters were extracted from the texts of court decisions: Administrative Law, Canceled of Appointment, Year, Fine_size, Article 2.9 Insignificance, Article 24.5 Excluding, Article 4.5 Expiration date, Extenuating circumstances, Aggravating circumstances, Repentance, Guilt admission, Assistance to police, voluntary reporting of an offence (Communication), not previously involved (First time), Have_a_baby, Continued_violation, Repeated offence (Second_time), Administrative penalty (Under_punishment).

Classification

This machine learning method demonstrates the likelihood of the outcome of a court case to overturn an administrative offence, depending on the circumstances of the case and the year of the decision. The task of classification was to predict the abolition of the fine for violation of the migration law Chapter 18 of the Administrative Code by means of gradient boosting and decision trees. The precision and recall metrics were used to evaluate the quality of the classification forecast.

Regression

The problem to predict the size of the fine was solved by regression with the help of random forest and gradient busting. Due to the fact that the classes were not balanced the automatic balancing of the model weights was applied. The mean absolute error (MAE) metric was used to evaluate the quality of the regression forecast.

B. Case Study Results

In the course of the research, the electronic data of 5 million court acts issued by courts in various regions of Russia were analyzed. The data were selected randomly. Of the judicial acts, 95.3 % concerned the imposition of penalties and 3.7 % concerned the termination of proceedings.

The most common administrative offense in the analyzed data is hooliganism (Article 20.1 of the Code of Administrative Offences of the Russian Federation), entailing in law enforcement practice an administrative fine from 500 to 1000 rubles or administrative arrest for 1 to 15 days. Common articles include an article on fire safety (20.4) and the article on migration (18).

The task of n-grams producing was resolved by using TF-IDF as it was described in the methods section. It allowed calculating the weights of each term in a document. The most important n-grams were filtered and used in the work (Fig. 2).

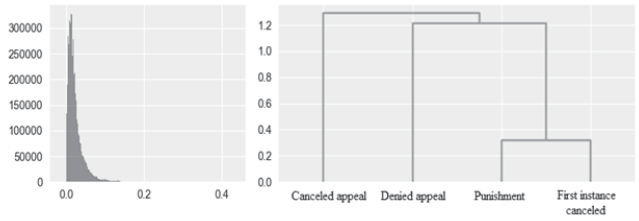

Fig. 2. The analysis of the court decisions texts

Correlation of a law article with a period of time is a dynamic indicator that clearly indicates the presence of significant changes in law enforcement practice, if the value of the correlation is different for different time periods (Figure 3). For the analysis of decisions on the migration law, 50438 decisions were used in the period from 2015 to 2019. As a rule, a changes that can be seen on the correlations of an article of the law and time periods are associated with significant changes in the law. By the example of the

correlation matrix (Figure 4) it can be seen that the offences provided by Articles 18.1, 18.2, 18.8, 18.10, 18.11, 18.15, 18.16 and 18.17 of the Code of Administrative Offences of the Russian Federation have no correlation with time periods. This means that significant and obvious changes in these years have not been identified for these articles, and the practice of applying these articles has not changed in these years.

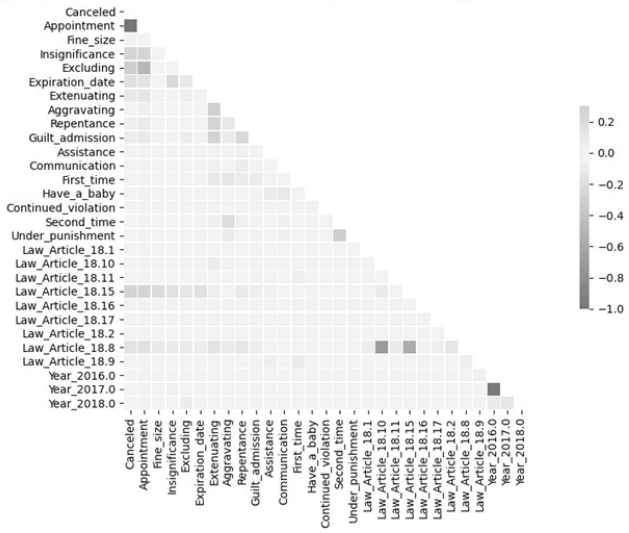

Fig. 3. Heatmap results of correlation analysis of court decisions data on migration law

This is confirmed by simple observation. The legislator made the last significant changes to Article 18.1 - in 2009, to Article 18.2 - in 2014, to Article 18.8 - in 2013 (in 2016 this article only singled out special parts with more severe penalties for the same offences committed in Moscow, St. Petersburg, Moscow and Leningrad regions), to Article 18. 10 - in 2015, in article 18.11 - in 2007 (in 2016 there was a technical change of the term in the article), in article 18.15 - in 2015 (in 2016 there was a technical change of the term in the article), in article 18.16 - in 2014, in article 18.17 - in 2013. These articles did not show any change in the values of the correlation for the time periods 2016, 2017 and 2018.

In contrast, article 18.9 of the Code showed a change in the values of correlation between 2017 and 2018 (zero correlation) compared to 2016 (positive correlation). In this case, we noted a dynamic indicator, which follows some significant change in the practice of administrative responsibility based on Article 18.9 of the Code. The presence of such changes is objectively confirmed by the fact that the legislator made changes to Article 18.9 of the Code in 2017 and 2018. Clarification of the nature of changes that occurred over time requires the use of other analytical tools. In addition, other methods allow to identify more complex changes in judicial and administrative practice, for which the simple correlation of the two indicators is not enough. It is also important to note that not all legislative changes significantly affect the practice of applying the articles of law. In particular, with regard to Articles 18.8, 18.11 and 18.15, this dynamic indicator did not appear, as the changes in the law were of a technical nature. In Article 18.8, in addition to the general case, some parts of the article specified private cases of violation, while in Articles 18.11 and 18.15 the outdated term was replaced by a current one, corresponding to the modern legislation. Thus, this indicator can show how serious the changes in the law were based on the real legal practice. The correlation of an article of the law with different circumstances mitigating or aggravating the penalty is an indicator of individualization of the penalty. Individualization of punishment is one of the most important principles of prosecution. Lack of individualization of punishment (zero correlation with each of the circumstances), as a rule, means violations in the process of law enforcement. No correlation is a normal practice only in cases when the law provides only one variant of punishment, without any alternatives. Otherwise, no correlation to any circumstances mitigating or aggravating the penalty means that the enforcer reduces the proceedings, avoids clarifying the facts of the case, and the penalty imposed is not individualized (in practice, in this case, a minimum penalty is imposed to avoid appealing the amount of the penalty). This violates the rules on the imposition of penalties (article 4.1 of the Code) and makes alternative penalties provided for by the legislator a "dead" norm. For example, article 18.1 provides various penalties. In particular, in parts 1 and 2 of this article, which are applied most frequently, the punishment for citizens is a fine of two to five thousand rubles. However, in practice, an administrative fine for this offence is imposed in the minimum amount (2,000 rubles). The correlation matrix shows that Article 18.1 has a zero correlation with each of the circumstances of the case that mitigate or aggravate the penalty, which is fully consistent with actual practice. In contrary, Articles 18.8 and 18.15 of the Code have a non-zero (positive or negative) correlation with many circumstances that affect the individualization of punishment.

Classification results to predict the cancellation of penalties for the violation of the migration law

To predict the cancellation of the punishment for the migration law violation, the classification problem was solved. Gradient busting gave the best result with Area Under Curve (AUC)=93. Figure 4 shows the nature of the impact (positive or negative) of various parameters of the case on the outcome of judicial review of the case.

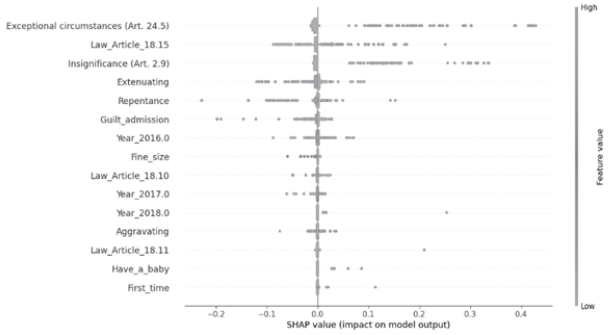

Fig. 4. Features importance distribution using SHAP values

For example, the establishment of any mitigating circumstances ("Extenuating") by the court is associated with the abandonment of the previously issued administrative

penalty order, while the cancellation of the order is associated with the absence of mitigating circumstances established by the court. This result is due to the fact that mitigating circumstances are established by the court to mitigate the penalty. Mitigating circumstances such as repentance and guilt admission are well explained: establishing these circumstances means that the person is indeed guilty of the offence (the person repents of the act or confesses guilt) and therefore the court refuses to set aside the earlier sentencing order. In contrary, the establishment of the circumstances precluding the proceedings ("Exceptional circumstances (Art. 24.5)") shows their high relevance to reversing an earlier ruling. The same result shows the determination of the insignificance of the offence (Art. 2.9), which entails exemption from administrative liability. Interestingly, the aggravating circumstances ("Aggravating") have no obvious connection either with the annulment of an earlier ruling or with the keeping of that ruling unchanged. Given that mitigating and aggravating circumstances under the law are equally part of the subject matter of proof in a case, this means that in practice the process of establishing mitigating circumstances is different from the process of establishing aggravating circumstances. Both the offender, who can obtain a less severe punishment thanks to them, and the court, who can obtain a legal and fair decision thanks to them, are interested in establishing mitigating circumstances, which are less likely to be appealed and revoked on the basis of the unfairness of the punishment imposed. For the same reasons, no one is interested in identifying aggravating circumstances that would lead to a heavier penalty, and they are identified for objective reasons. This method allows to reveal the importance of the influence of any parameters of the case on the result of its resolution, and for clarification and interpretation of the results obtained it is acceptable to use both traditional methods and other computational tools. Thus, foreign citizens are often brought to justice under the administrative offences in question. It is therefore in this category of cases that the fact that the offender has underage children may, in some cases, have a major impact on the reversal of an earlier sentencing order (some red dots in positive terms on the line "Have a baby"). The meaning of this significance is that a foreign offender may have a child with Russian citizenship, and in this situation the court sometimes finds some reason to overturn an earlier sentencing order, acting in the interests of an international family. Some dependencies are more complex. In particular, the fine line ("Fine-size") shows that average fines (purple dots in negative values) correlate well with a refusal to review an earlier ruling, while low and high fines correlate well with a cancellation of an earlier ruling.

Regression results to predict the amount of a fine for violating the migration law

The model to predict the size of the fine was solved the regression with the help of random forest and gradient busting. As a result, the gradient boosting gave a better result Test-mae:1290.87732 1290.8781587419678. In the Fig. 5 the array of cases of the category under consideration shows the significance of different parameters of the case for determining the amount of penalty.

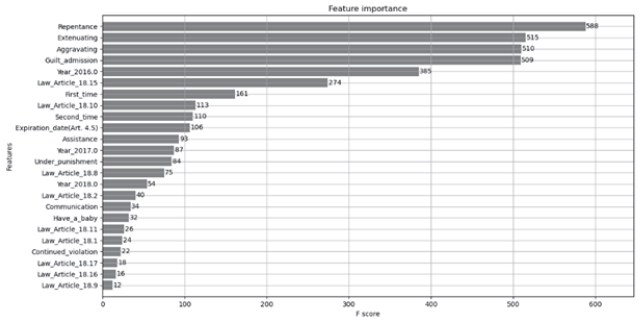

Fig. 5. Feature importance for the fine amount

For example, the mitigating and aggravating circumstances ("Extenuating" and "Aggravating") are almost equally important in determining the amount of a fine, but the different types of mitigating and aggravating circumstances vary considerably: for example, repentance is a more important mitigating circumstance, with a score of 588, than assistance in investigating an offence ("Assistance"), with a score of 93. The main reasons for these differences are the habituality of such circumstances in legal practice. "Repentance" is very often established by the court by receiving a response from the offender to the standard question: "Do you repent of what you have done? For the offender, this "repentance" is to obtain a lighter penalty and only the offender's words are proof of repentance, as in the case of a Guilt admission. "Facilitation" of justice is established on the basis of the real actions of the offender, which are rarely recorded and even less frequently documented. Therefore, "aid" is rarer and more unusual for the court and has less impact on the amount of the fine than "remorse", although it has immeasurably greater social utility.

However, this method often does not allow setting the direction of injection of some parameters on the other. On the decision tree (Figure 6) we can see a group of articles in the Chapter 18 of the Code (Articles 18.1, 18.2, 18.8, 18.9, 18.10, 18.11, 18.15, 18.16 and 18.17). The resulting tree shows that this method can be successfully used not only on one article (part of an article) of the Code, as it was shown in the authors' early works [2], [33], [39]. This decision tree is built using not only the actual circumstances of the case but also different articles of the Code and time periods (years).

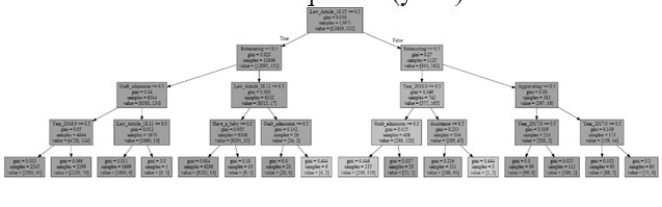

Fig. 6. Results of the decision tree classification for the abolition of punishment

The resultant tree showed that on the basis of large arrays of cases it is possible to show similarity in solving legal issues (in this case: determination of the size of the fine) not only for one type of offence, but also for a group of rights violations. An indicator of the specificity of the legal solution in this case is the article of the Code (type of offence), which is at the base of the branching of the tree (Article 18.15) and at lower levels (Article 18.11). Non-specific decisions do not depend on the

type of offence, therefore, other articles of the Code (18.1, 18.2, 18.8, 18.9, 18.10, 18.16 and 18.17) do not appear in the tree. It can be seen on the decision tree that the period of time (2016), which determined the classification significance of one of the two circumstances: assistance in disclosure of the offence for 2016, admission of guilt for other years, is important for the solution of issues under Article 18.15 (right part of the tree).

VII. Discussion and conclusion

In this work we have developed a method and a set of models of structuring and analysis of legal data. This was implemented as a service to provide its functions to the users. The efficiency of the developed method was proved, and the utilization of the obtained results was used to produce recommendations for the improvement of administrative practice. Each of the considered areas to improve administrative regulation is based on a thorough empirical study based on the data of electronic court decisions. Comparison of the developed system with the state of the art can be done considering its efficiency and performance of the machine learning models. The resulting AUC = 93 reached on the test dataset places our solution among the top performing systems. For example [22] provided AUC=85 and [23] AUC = 91. Our solution also provides a better interpretation of the results to provide more value to the potential users. Considering the level of interest in administrative process reform, this research will contribute to the development of methods for improving administrative legislation and scientific understanding of law as a social tool. In this article we show how using the various articles of the Russian Code of Administrative Offenses as an example it is possibile to consistently use different methods for analyzing legislation and law enforcement on the basis of various static and dynamic indicators. This allowed gaining more complete knowledge about the law and methods of its interpretation.

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