Associative Rule Mining for the Assessment of the Risk of Recidivism

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Abstract

Information technologies, such as big data analytics (data mining, and predictive analytics) are rapidly developing and penetrating into critically important areas of modern technocratic society, including law enforcement and security sectors. Successful applications of artificial intelligence (AI) are able not only to provide informational support for decision-making, but also to replace the person himself in this process. Global digitization has also affected criminal justice in recent years. The justice system adapts to modern challenges and megatrends using digital platforms and data science.

Solving crimes is a complex task and requires significant resources and expertise. Data mining models can provide effective solutions for solving complex non-standard problems of crime detection. AI algorithms are increasingly used in predictive justice to support judicial decision-making, in particular the qualification of crimes and their relevance to the criminal process. Text Mining algorithms provide reliable support in the formation of the evidence base, judicial analytics, and reasonable decision-making in criminal proceedings.

Predictive machine learning algorithms are not always 100% accurate, but the criminal justice system is becoming more and more technologically complex. Its effective functioning includes the processing of large volumes of unordered and unstructured data. Nowadays, association rules, i. e. one of the important machine learning models, are widely used to identify patterns and discover new knowledge in such masses of information. The work uses associative rule mining for the extract correlations and co-occurrences between the historical crime information of convicted people. An associative rule mining model was built to search for non-obvious interesting connections between historical crime information of convicted and repeated offenses. The frequent item sets, which are a combination of individual characteristics of convicts who commit repeated criminal offenses, and the strong association rules, have been revealed. The obtained results give grounds for asserting that early dismissals and suspended convictions are the main factors (antecedents), that cause the risk of recidivism (consequent).

Keywords 1

Crime data mining, associative rule, artificial intelligence, decision-making, safety, risk of recidivism

1. Introduction

Traditionally, the task of law enforcement agencies is to arrest criminals already after committing crimes. However, the emergence of new technologies, such as data mining and artificial intelligence, has created new unique opportunities to truly predict and prevent crimes. New tools create effective

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solutions for collecting and interpreting connections and patterns in data from various open and closed sources, such as crime records, geospatial images, social network information, news feeds, etc.

This article is a continuation of the cycle of works on the issue of using methods and data mining models to support the decision-making process in criminal justice [1, 2, 3, 4]. Nowadays, predictive policing already actively uses predictive algorithms of artificial intelligence to identify criminals by individual facial features, assess the risk of recidivism, predict possible places of crime, search for information in social networks, etc. AI systems are used at various stages of criminal proceedings, for example, to determine the possibility of parole or participation of the accused in the probation system, calculation of the optimal term of imprisonment, and determination of the level of danger of the defendant to society.

Solving the problems of assessing the risk of crime and recidivism requires special attention at present, since it is the individuality of the prisoner, and not the fact of the crime itself, that poses a significant threat to the personal safety of citizens and society in general. The convicts make up a considerable part of the military contingent participating in Russia's open military attack on Ukraine [5, 6]. They commit new terrible crimes. The aim of our research is to create an associative rule mining model, which, based on known individual characteristics of convicts (historical crime data of convicted), reveals implicit interesting connections, that are the sufficient reason for the repeated offenses. The historical crime information of convicted is stored in large databases and may contain hidden knowledge that is interesting and useful. The analysis of such information consists in establishing regularities and discovering new interesting knowledge from existing data sets. The exponential growth of modern databases' volumes has necessitated the use of scalable algorithms for information analysis. For our applied research, we used one of the common methods of extracting new knowledge – association rule algorithms.

2. Related work

The issue of applications of the latest information technology tools, such as data mining and artificial intelligence, in criminal justice has recently been studied by many scientists [7, 8, 9, 10, 11]. N. Jabeen and P. Agarwal presented an overview of various research works devoted to the application of data mining methods in crime analysis [12]. O. Ogochukwu, and O. Forster, using the data mining tools, real-time and location data, developed a system that can determine which category of crimes is most likely to occur in a specific place at a specific time [13]. A. Sanghani, C. Sampat, V. Pinjarkar. analyzed the problems of applying clustering technique for criminal prediction [14]. P. Saravanan et al. studied data analysis methods for predicting crime based on various demographic, socio-economic, spatio-temporal and geographical factors [15]. A. Idder, and S. Coulaux considered AI as an integral part of the criminal justice system, which is used for analytics, forecasting, a crime-solving, and recidivism. [16]. In [2], the scoring model is proposed for assessing the risks of recidivism by criminals based on individual statistical and dynamic data of convicts. In [1], the method of binary logistic regression was used to predict the probability of repeated crimes by convicts in the future. D. Baker et al. studied the use of artificial intelligence to solve law problems, in particular in criminal justice [17]. S. Greenstein considered the problem of the impact of artificial intelligence technologies on ensuring the transparency and fairness of the justice system and compliance with the rule of law [18]. F. Dakalbab et. all investigated artificial intelligence strategies in crime prediction. They evaluated the existing models according to various criteria, including the choice of analysis method, its advantages, disadvantages, and limitations, types of investigated crimes, forecasting techniques, performance indicators and evaluation of results, and development prospects [19]. A. Završnik considered the risks created by artificial intelligence systems in the field of criminal justice, such as case law and some of the human rights affected, and proposed solutions for their elimination [20]. A. Wyner et al. analyzed different approaches to automatic profiling and analysis of evidence in criminal proceedings [21]. Ju. Xu developed predictive models for predicting court sentences, applying the concepts of big data and data mining [22]. H. Jantan and A. Jamil used historical data on crime activities for retrieval patterns and trends of crimes for future prevention actions by applying the apriori algorithm from the association rule mining method [23]. Caliskan et al. created associative rules for determining time intervals, areas, types of crimes, and frequency of events based on various data related to the subject of the crime, which was obtained in real-time, by tools of data mining methods [24]. In [3], the concept of using text mining methods for fast and qualitative analysis of electronic text documents is proposed. A decision tree model using Chi-square automatic interaction detector growing method was developed for the classification of legal texts.

Crime is a social problem and costs society too much not only from an economic point of view. Any research that helps to solve crimes faster is worthwhile. The identification of non-obvious connections and regularities in the data set and the construction of computer models for decision-making and problem-solving in criminal justice are especially relevant.

3. Research Methodology

Our research is carried out as part of the development of a unified concept of information and analytical support for the criminal justice system of Ukraine. Sections 3.1 and 3.2 present the main results obtained in previous works [1, 2]. Applied models are built based on individual and statistical data on 13,010 convicts serving sentences in Ukrainian penitentiaries.

3.1. A binary logistic regression model to predict the probability of convicted criminal recidivism

The following equation of the regression logistic model is constructed [1]:

$$\hat{Y} = -0.55A - 0.21Te - 5.45Suc + 5.6Mc + 5.75Cm + 5.61Sc + 5.8Ps + 1.7Ed - 8.17, \quad (1)$$

where *A* – Age1, *Te* – type of employment, *Suc* – suspended convictions, *Mc* – Minor crimes, *Cm* – crimes of medium gravity, *Sc* – serious crimes, *Ps* – particularly serious crimes, *Ed* – early dismissals.

The built model has high sensitivity *Se* and specificity *Sp*:

$$Se = \frac{TP}{TP + FN} \cdot 100\% = \frac{6308}{6308 + 88} \cdot 100\% = 99\%, \quad (2)$$

$$Sp = \frac{FP}{FP + TN} \cdot 100\% = \frac{6402}{6402 + 106} \cdot 100\% = 98\%, \quad (3)$$

The parameters *TP*, *FP*, *TN*, and *FN* are presented in Table 1 below.

Table 1
The number of true and false predicted results of the logistic model

Parameter	Parameter value
true positive, *TP*	6308
false positive, *FP*	6402
true negative, *TN*	106
false negative, *FN*	88

The developed model provides accurate forecasts both for cases of repeated criminal offenses and for cases of non-recurrence of criminal relapses. It can be used to predict the likelihood of criminal cases' recidivism based on statistical and dynamic inmate data.

3.2. A scoring model for assessing the risk of recidivism by criminals

We have detected the most significant individual characteristics of prisoners for forecasting the risk of criminal recidivism (Table 2).

Table 2
Table of predictor importance for dependent variable recidivism

	Predictor importance	
Variable	Variable Rank	Importance
Number of suspended convictions	100	1.00
Number of particularly serious crimes	41	0.41
Aage at the time of the first conviction	39	0.39
Availability of early dismissals	26	0.26
Age at the time of the first conviction	25	0.25
Sex	25	0.25
Education	9	0.09
Marital status	7	0.07
Type of employment at the time of conviction	4	0.04
Place of residence to the actual degree of punishment	3	0.03
Age	3	0.03
Motivation for dismissal	2	0.02

The following data mining and machine learning algorithms were used to build the predictive model (Fig. 1):

- Standard Classification Trees with Deployment;
- Standard Classification CHAID with Deployment;
- Boosting Classification Trees with Deployment;
- Intelligent Problem Solver with Deployment;
- Support Vector Machine with Deployment (Classification);
- MARSplines for Classification with Deployment.

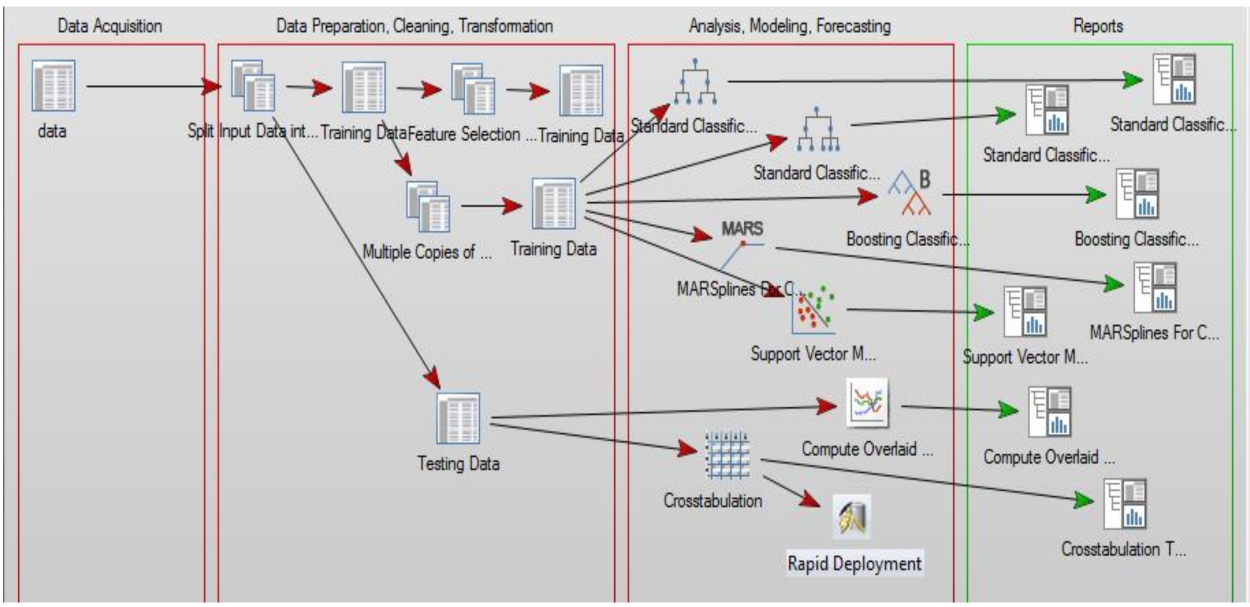

Figure 1: Data Miner workspace

The classification matrix (Table 3) presents the number of observations that were classified correctly and incorrectly. The constructed model can correctly predict the propensity for criminal recidivism with 97% accuracy.

Table 3
Matrix of predicted and observed frequencies of output values for the test set

Classification Matrix		
	Observed 0	Observed 1
Predicted 0	141	7
Predicted 1	8	341

To support effective decisions in criminal justice, a unified information system is needed, which should include various computer models based on data mining and AI algorithms. Only the application of different methods to data analysis can provide an understanding of the problem as a whole, obtaining reliable results or verifying previous conclusions. This especially applies to non-trivial tasks of extracting non-obvious connections, new patterns, and interesting associations. One of the methods used to solve such difficult tasks in criminal justice is associative rule mining.

3.3. Associative rule mining

Association rules are a key concept in data mining [25, 26]. The task of association rules is to find patterns in the flow of data. Association occurs when several events are connected to each other. Hidden connections are revealed in seemingly unrelated data. These relationships are if-then rules. Those of them that exceed a given limit are considered interesting. Such rules make it possible to perform actions based on certain patterns. They also provide support in making and explaining decisions.

The task of association rule mining is defined as.

Let $I = \{i_1, i_2, \dots, i_n,\}$ – set of n attributes (item), where n – is the total number of attributes.

Let $T = \{t_1, t_2, \dots, t_m,\}$ – set of transactions (database), where m – is the total number of transactions.

Transaction (multiple events occurring simultaneously) in D is a subset of the set I.

A rule is defined as:

$$X \Rightarrow Y, \tag{4}$$

where $X, Y \subseteq I$.

Each rule consists of two different itemsets X (antecedent) and Y (consequent).

To select interesting rules from the set of all possible rules, restrictions are imposed on different ways of measuring significance and interest. The most famous limitations are the minimum limits of support and confidence.

Let X is the itemset, $X \Rightarrow Y$ is the association rule, and T is the set of transactions.

Support determines how often a transaction appears in the database. This is the part of the transaction containing antecedent and consequent. Support X relative to T is calculated as the share of transactions t in a set of transactions containing a subset of X:

$$supp(X) = \frac{|\{t \in T; X \subseteq t\}|}{|T|}, \tag{5}$$

Confidence indicates how often the rule is executed. This is a measure of the accuracy of the rule, which is defined as the ratio of the number of transactions containing the antecedent and consequent to the number of transactions containing only the antecedent. The confidence value in the rule $X \Rightarrow Y$ relative to the set of transactions T is the fraction of transactions that contain X and Y:

$$conf(X \Rightarrow Y) = \frac{supp(X \cup Y)}{supp(X)}. \quad (6)$$

If support and confidence are large enough, it can be said with a high probability that any future transaction that includes the antecedent will also contain the consequent.

Lift (interest, improvement) is the ratio of the frequency of the antecedent occurrence in transactions that also contain the consequent to the frequency of occurrence of the consequent in general. Lift rules are determined by the formula:

$$Lift(X \Rightarrow Y) = \frac{supp(X \cup Y)}{supp(X) \times supp(Y)}. \quad (7)$$

This is the ratio of the observed confidence to the expected if X and Y were independent. It is believed that lift is a generalized measure of the relationship between two datasets: when $L > 1$, the relationship is direct, when $L = 1$, there is no relationship, when $L < 1$, the relationship is inverse. Lift is used to further limit the set of associations under consideration by setting of significant. Associations below the set limit of significant value are rejected.

Conviction is a measure of the degree of implication of a rule. Conviction is defined as

$$conv(X \Rightarrow Y) = \frac{1 - supp(Y)}{1 - conv(X \Rightarrow Y)}. \quad (8)$$

A conviction can be interpreted as the ratio of the expected frequency that X appears without Y (the frequency that the rule makes an incorrect prediction) if X and Y are independent, divided by the observed frequency of incorrect predictions.

The algorithm for finding associative rules usually consists of two separate steps:

1. Limit value of minimum support is used to find all frequency of item in database (frequent if-then associations).
2. The restriction on the minimum confidence is applied to the frequency of itemset for the formation of rules.

Association rules is not a trivial task at all. As the number of items increases, the number of potential itemsets increases exponentially, which causes algorithmic complexity when finding frequent itemsets. Like most data mining methods, this method makes it possible to transform a potentially huge amount of information into a small and understandable set of statistical indicators. The rules do not distinguish individual preferences, but rather find connections between a set of elements of each individual transaction.

4. Data selection and description

When conducting applied research, a visual environment was used for the development of RapidMiner Studio workflows. The software is designed for predictive analytics and includes data science and machine learning capabilities. Database was formed on the basis of crime records of 13,010 prisoners serving sentences in penitentiary institutions of Ukraine. To identify associative rules between historical crime information of convicted and repeated offenses, a data set was used, which contained the following attributes:

- nominal:
  - recidivism (1 – yes, 0 – no);
  - sex (1 – male, 2 – female);
  - marital status (1 – single, 2 – married);
  - education (0 – incomplete secondary, 1 – secondary, 2 – special secondary, 3 – incomplete higher, 4 – higher);

- place of residence (1 – rural area, 2 – urban area);
- type of employment (0 – unemployed, 1 – part-time, 2 – full-time);
- early dismissals (1 – yes, 0 – no);
- motivation for dismissal (1 – yes, 0 – no);

– numerical:

- age;
- age1 (at the time of the first actual degree of punishment);
- age2 (at the time of the first suspended or actual sentence);
- real convictions (number of real convictions);
- suspended convictions (number of suspended convictions).

Data set includes 13,010 examples. Example is characterized by its attributes and has specific values that can be compared with other examples. Examples are rows of the data set table containing historical crime information of convicted.

To implement associative rule mining algorithms, a process consisting of the following operators is compiled (Fig. 2):

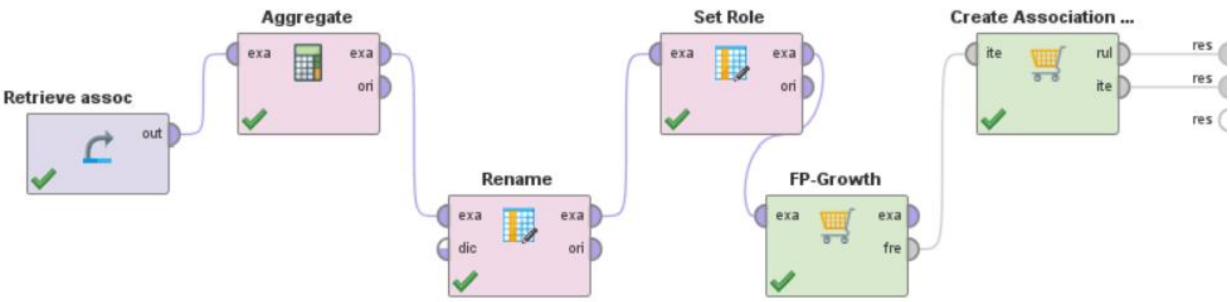

Figure 2: Association rules mining process in RapidMiner

- The Retrieve operator loads a data set into the process.
- The Aggregate operator forms a new example set (a table created from attributes (columns) and examples (rows)), which is the result of applying the aggregation function (average, sum, count, min, max etc.) to the input data set.
- The Rename operator is intended for renaming one or more attributes of the input data set.
- The Role operator describes how other operators handle this attribute. In our model, we chose an attribute with the role of id, which acts as a unique identifier for each of the examples. The FP-Grown operator computes frequently-occurring itemsets in a data set, using the FP-tree data structure (represents the data set in tree form).
- The Create Association Rules operator produces a set of association rules from the calculated set of frequent itemsets.

Association Rules make it possible to find non-obvious patterns between related events and discover all such relationships between elements from huge databases.

Data mining model creation with the following parameters values that specifies the criterion which is applied for the selection of association rules (Table 4):

Table 4.
The criterion which is used for the selection of rules

Criterion	Min criterion value
confidence	0.1
lift	0.8
conviction	0.8
gain	0.8
Laplace	0.8
ps	0.8

The gain is computed by applying the gain theta parameter.
The Laplace is computed by applying the Laplace k parameter.
The ps criteria is applying for rule selection

5. Results and Discussion

As a result of the compiled associative rule mining model, the frequent item sets (Fig. 3) and the association rules (Fig. 4–6) were obtained.

Support	Item 1	Item 2	Item 3	Item 4
0.984	real convictions	recidivism		
0.935	recidivism	early dismissals		
0.815	recidivism	suspended convictions		
0.935	real convictions	recidivism	early dismissals	
0.815	real convictions	recidivism	suspended convictions	
0.782	recidivism	early dismissals	suspended convictions	
0.782	real convictions	recidivism	early dismissals	suspended convictions

Figure 3: Frequent item sets (FP-Grown)

The developed data mining model gives reasons to claim that in the analyzed record crimes, the most frequent individual characteristic among those sentenced to real convictions is "recidivism" (support = 0.984). Therefore, a significant share of prisoners, information about which is stored in the studied dataset, already had previous convictions. The most frequent combinations of investigated features are "recidivism, early dismissals" and "recidivism, suspended convictions". This indicates that the majority of prisoners who committed repeated criminal offenses had early dismissals (support = 0.935) and suspended convictions (support = 0.815) in the past (Fig. 3).

Association No. 6, 20, and 37 cannot be attributed to associative rules, since lift = 1 (relation between antecedent and consequent is absent). All other identified associative rules are strong, as they have high support (≥ 0.782) and high confidence (≥ 0.829). They demonstrate a strong positive correlation in the data set and often occur when applied (Fig. 4).

No.	Premises	Conclusion	Support ↓	Confidence	LaPlace	Gain	p-s	Lift	Conviction
37	real convictions	recidivism	0.984	0.984	0.992	-1.016	0	1	1
20	real convictions	recidivism, early dismissals	0.935	0.935	0.968	-1.065	0	1	1
41	early dismissals	recidivism	0.935	0.991	0.996	-0.952	0.007	1.008	1.887
42	early dismissals	real convictions, recidivism	0.935	0.991	0.996	-0.952	0.007	1.008	1.887
43	real convictions, early dismissals	recidivism	0.935	0.991	0.996	-0.952	0.007	1.008	1.887
6	real convictions	recidivism, suspended convictions	0.815	0.815	0.907	-1.185	0	1	1
34	suspended convictions	recidivism	0.815	0.981	0.991	-0.847	-0.003	0.997	0.831
35	suspended convictions	real convictions, recidivism	0.815	0.981	0.991	-0.847	-0.003	0.997	0.831
36	real convictions, suspended convictions	recidivism	0.815	0.981	0.991	-0.847	-0.003	0.997	0.831
10	early dismissals	recidivism, suspended convictions	0.782	0.829	0.917	-1.105	0.014	1.018	1.085
11	early dismissals	real convictions, recidivism, suspended conv...	0.782	0.829	0.917	-1.105	0.014	1.018	1.085
12	real convictions, early dismissals	recidivism, suspended convictions	0.782	0.829	0.917	-1.105	0.014	1.018	1.085
21	suspended convictions	recidivism, early dismissals	0.782	0.942	0.974	-0.879	0.005	1.007	1.108
22	suspended convictions	real convictions, recidivism, early dismissals	0.782	0.942	0.974	-0.879	0.005	1.007	1.108
23	real convictions, suspended convictions	recidivism, early dismissals	0.782	0.942	0.974	-0.879	0.005	1.007	1.108
38	early dismissals, suspended convictions	recidivism	0.782	0.990	0.995	-0.798	0.005	1.006	1.581
39	early dismissals, suspended convictions	real convictions, recidivism	0.782	0.990	0.995	-0.798	0.005	1.006	1.581
40	real convictions, early dismissals, suspended convic...	recidivism	0.782	0.990	0.995	-0.798	0.005	1.006	1.581

Figure 4: Top 18 rules sorted by maximum support value

The following association rules were detected:

```
Association Rules
[real convictions] --> [recidivism, early dismissals, suspended convictions] (confidence: 0.782)
[real convictions] --> [early dismissals, suspended convictions] (confidence: 0.790)
[recidivism] --> [early dismissals, suspended convictions] (confidence: 0.795)
[recidivism] --> [real convictions, early dismissals, suspended convictions] (confidence: 0.795)
[real convictions, recidivism] --> [early dismissals, suspended convictions] (confidence: 0.795)
[real convictions] --> [recidivism, suspended convictions] (confidence: 0.815)
[recidivism] --> [suspended convictions] (confidence: 0.828)
[recidivism] --> [real convictions, suspended convictions] (confidence: 0.828)
[real convictions, recidivism] --> [suspended convictions] (confidence: 0.828)
[early dismissals] --> [recidivism, suspended convictions] (confidence: 0.829)
[early dismissals] --> [real convictions, recidivism, suspended convictions] (confidence: 0.829)
[real convictions, early dismissals] --> [recidivism, suspended convictions] (confidence: 0.829)
[real convictions] --> [suspended convictions] (confidence: 0.831)
[recidivism, early dismissals] --> [suspended convictions] (confidence: 0.836)
[recidivism, early dismissals] --> [real convictions, suspended convictions] (confidence: 0.836)
[real convictions, recidivism, early dismissals] --> [suspended convictions] (confidence: 0.836)
[early dismissals] --> [suspended convictions] (confidence: 0.838)
[early dismissals] --> [real convictions, suspended convictions] (confidence: 0.838)
[real convictions, early dismissals] --> [suspended convictions] (confidence: 0.838)
[real convictions] --> [recidivism, early dismissals] (confidence: 0.935)
[suspended convictions] --> [recidivism, early dismissals] (confidence: 0.942)
[suspended convictions] --> [real convictions, recidivism, early dismissals] (confidence: 0.942)
[real convictions, suspended convictions] --> [recidivism, early dismissals] (confidence: 0.942)
[real convictions] --> [early dismissals] (confidence: 0.944)
[recidivism] --> [early dismissals] (confidence: 0.951)
[recidivism] --> [real convictions, early dismissals] (confidence: 0.951)
[real convictions, recidivism] --> [early dismissals] (confidence: 0.951)
[suspended convictions] --> [early dismissals] (confidence: 0.951)
[suspended convictions] --> [real convictions, early dismissals] (confidence: 0.951)
[real convictions, suspended convictions] --> [early dismissals] (confidence: 0.951)
[recidivism, suspended convictions] --> [early dismissals] (confidence: 0.960)
[recidivism, suspended convictions] --> [real convictions, early dismissals] (confidence: 0.960)
[real convictions, recidivism, suspended convictions] --> [early dismissals] (confidence: 0.960)
[suspended convictions] --> [recidivism] (confidence: 0.981)
[suspended convictions] --> [real convictions, recidivism] (confidence: 0.981)
[real convictions, suspended convictions] --> [recidivism] (confidence: 0.981)
[real convictions] --> [recidivism] (confidence: 0.984)
[early dismissals, suspended convictions] --> [recidivism] (confidence: 0.990)
[early dismissals, suspended convictions] --> [real convictions, recidivism] (confidence: 0.990)
[real convictions, early dismissals, suspended convictions] --> [recidivism] (confidence: 0.990)
[early dismissals] --> [recidivism] (confidence: 0.991)
[early dismissals] --> [real convictions, recidivism] (confidence: 0.991)
[real convictions, early dismissals] --> [recidivism] (confidence: 0.991)
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Figure 5: Description of the associative rules

The developed data mining model explains the identified strong rules. From the obtained results, it can be concluded that repeated offenses are most often found in historical crime information of convicted persons who previously had suspended sentences or were released from prison on probation.

The identified associative rules confirm the results obtained in previous works [1, 2, 3, 4] and can provide important information to support decision-making in criminal justice. For example, regarding the expediency of applying a measure of punishment in the form of a suspended sentence or the possibility of probation for prisoners based on their historical crime records.

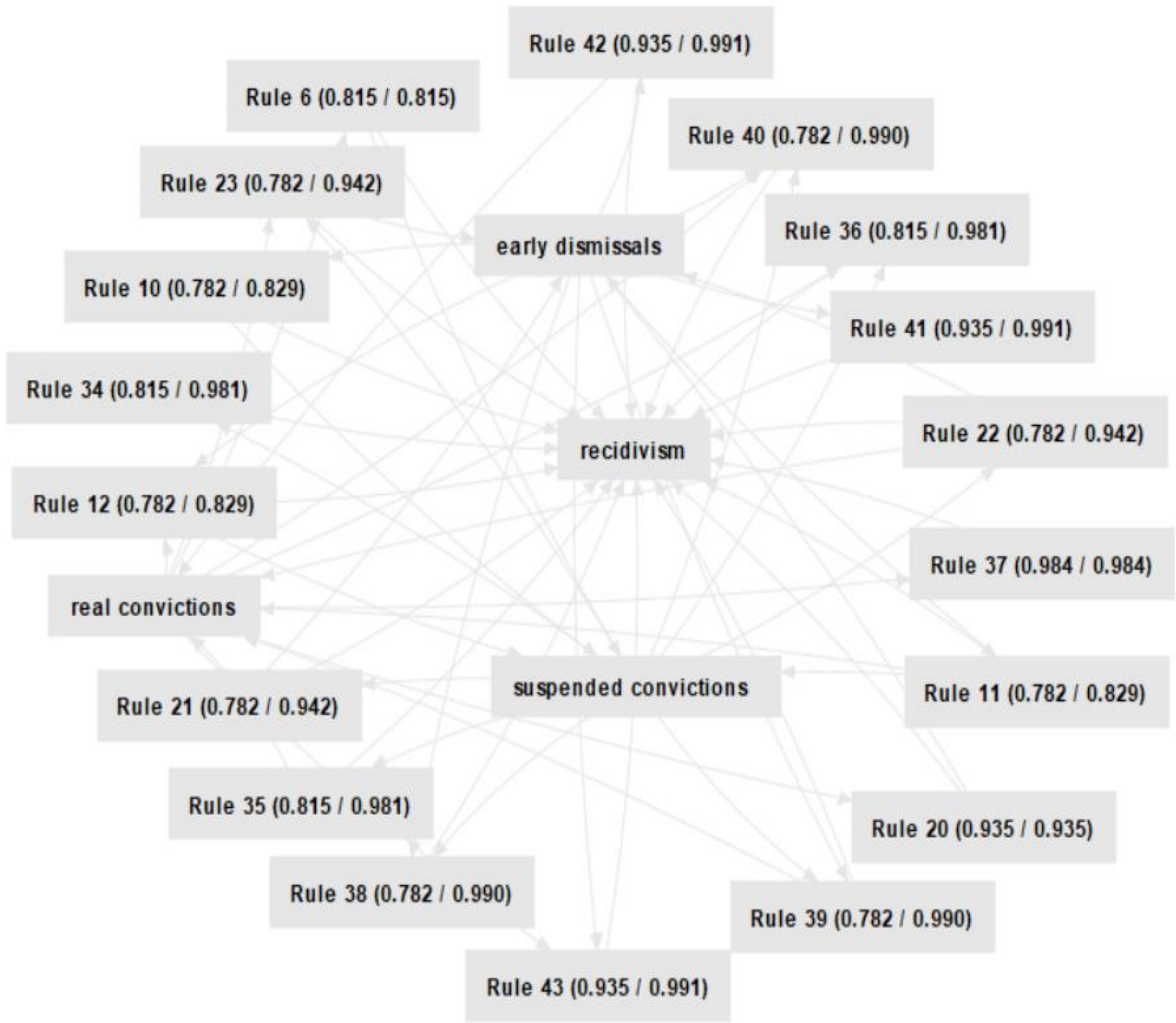

Figure 6: Drawing of rules

6. Conclusion

Measures aimed at ensuring the safety of individuals and society should be focused on preventing the commission of criminal offenses, and not on the disclosure of offenses that have already been committed. This is a proactive method, which consists in predicting the commission of criminal offenses in the future, including relapses. Nowadays, computational criminology is actively developing. It is an interdisciplinary science that uses computational methods and computer models to improve understanding of non-obvious connections and complex problems, and to develop effective solutions in the field of criminal justice. To prevent future crimes, law enforcement agencies should use crime data mining more actively.

Our case study was conducted on the basis of an actual data set from the criminal records of 13,010 convicts in Ukraine. We applied the Rapid Miner tool to the FP-Growth algorithm and compiled an associative rule mining model. Frequent item sets were identified and 43 associative rules were generated, which can explain non-obvious connections between crime record information of convicted and repeated crimes. It was established that the main signs that provoke the risk of recidivism are probations and suspended convictions. Modern prisons protect society from dangerous criminals, but they do not make them law-abiding. The leniency of the justice system, in particular the application of suspended convictions and the use of probations, gives the accused more hope for impunity than a chance for correction. This information may be relevant for criminal justice bodies when solving issues of parole, preventing criminal offenses, reducing the level of crime, and ensuring the internal security of the state. In general, machine learning methods and artificial intelligence systems will probably not become a panacea for the criminal justice system, but they can provide significant advantages in choosing an effective strategy for conducting criminal proceedings and optimizing the activities of justice authorities. The continuation of our research will be using prediction machine-learning models for identifying significant factors affecting the propensity of convicts to commit criminal recidivism.

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