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Cahier 2024-4

Forecasting for the justice system

An exploration of different algorithms

Summary

Kennisinstituut voor de rechtsstaat

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Cahier
De reeks Cahier omvat de rapporten van onderzoek dat door en in opdracht van het Wetenschappelijk Onderzoek- en Datacentrum is verricht. Opname in de reeks betekent niet dat de inhoud van de rapporten het standpunt van de Minister van Justitie en Veiligheid weergeeft.

Summary

Forecasting for the justice system

An exploration of different algorithms

Policymakers would like more insight into the demand for and (social) costs of crime, law enforcement and conflict resolution. It is therefore important to understand future trends in this area so that the best possible policy and financial decisions can be made. Forecasting models can be used for this purpose. Many years ago, the Forecasting Model for the Justice System (PMJ) was developed for the ministry of Justice and Security. This report examines the feasibility and usefulness of modernizing the PMJ using new developments in data and algorithms.

Forecasting model for the judicial system

Currently, forecasts about recorded crime, suspects and everything that follows, and conflict resolution are made with the PMJ. This model includes virtually the entire judicial system, including (police) investigation, prosecution and sentencing, sanctions, prisons, probation, subsidized legal aid in criminal cases and victim care. In addition, the model also includes (legal aid in) civil justice, administrative justice, legal aid in civil and administrative cases, and the detention of illegal immigrants. The judicial system can be viewed as a network. The PMJ uses demographic and economic forecasts to forecast the inflow at the beginning of the network, such as recorded crime. This forecast is then used to make forecasts of the inflow of cases at the Public Prosecution Service, and thus forecasts for the inflow at the courts and subsequently forecasts for the required sanction capacity. The PMJ is a combination of structural models, stock-flow models and time series models and includes approximately 6,600 equations. The parameters of the theoretical model are estimated using regression analysis on annual data. The result is an empirical model with which forecasts can be generated, which serve as a basis for a large part of the budget of the Ministry of Justice and Security.

Previous external evaluations show that the PMJ is well constructed and that users do not need a radically different model. But the current PMJ was designed in a period when the availability of microdata was limited, and a number of techniques were often theoretically known but could not be implemented due to limitations in computer technology. It is therefore useful to investigate whether there have been developments in recent years in the field of data and forecasting techniques that can provide more or different insights.

Limitations

The purpose of the PMJ is to make estimates of the capacity needs of the judicial system. The PMJ assumes that the entire capacity requirement can be financed. There are therefore no budget restrictions in the PMJ. The PMJ also takes chain effects into

account. Only amounts are forecasted, such as number of cases or number of suspects or number of sanctions. The PMJ does not include prices. The PMJ forecasts the items on which judicial organizations are financed. This varies per organization and is determined by the organizations themselves in consultation with the Ministry of Justice and Security and not by the PMJ. The PMJ follows these decisions. The PMJ does not determine what type of products or services or how organisations should be financed, but only how much should be financed, given what and how. If the method of financing is adjusted, the PMJ will be adjusted. A condition for the PMJ is that the criteria on which finances are provided, are quantifiable and measurable. Because the method of financing is a decision made outside the PMJ, this report will not discuss it further. The estimates themselves and their accuracy are also not discussed here. These can be found in other WODC-reports. The focus of this report is on models that can be used to forecast trends for (long-term) strategic purposes and not on predictive models for operational or forensic purposes, such as predictive policing or predictive sentencing.

Research question and preconditions

During the 2019 budget debate, the Minister for Legal Protection promised that he is willing to take another look at the PMJ. It was decided to take a two-track approach to revise the current PMJ. Track 1 concerns maintenance of and minor improvements and additions to the current PMJ. Track 2 concerns fundamental research into methods and techniques for better estimates. Track 2 is divided into three stages. In the first stage, an inventory was made of the needs of the end users of the PMJ. This stage was completed in 2020. The second stage examined the extent to which new developments in the field of data and techniques could be used in the PMJ. In the third stage, some promising techniques will be further developed in the form of pilots.
This report reports on the second stage. A large number of techniques were examined that could potentially be relevant for the PMJ. This means that with this selection of techniques the goal of the PMJ could in principle be achieved, namely making estimates of the capacity needs of the judicial system and forecasts for budget purposes. Techniques that are not suitable for this purpose have been ignored. The techniques have been assessed on the following aspects:

1. *Explainability of the algorithm from a non-technical point of view*. How easy is it to explain in simple terms what the algorithm does? In short, how intuitive is the algorithm?
2. *Simplicity of the algorithm*. How simple is the algorithm from a mathematical/statistical point of view?
3. *Implementability*. How much work does it take to implement the algorithm?
4. *Domain knowledge*. Is it possible to introduce domain knowledge into the algorithm?
5. *Network consistency*. Is it possible to use an algorithm to create a network-consistent model, that is, a model in which the outflow of one partner constitutes inflow for the next partner?
6. *Time component*. Is it possible to include a time component in the algorithm? That is, can the algorithm dynamically make a forecast for the (medium) long term or should some parts be assumed constant?
7. *Dealing with noise in the data*. Can the algorithm deal with noise in the data or does the quality of the data have to be very high?

8 *Privacy*. To what extent are micro-data necessary or can the algorithm also be applied to aggregated data? And if micro data is chosen, can the results be aggregated in such a way that they are suitable for further processing in aggregated model?
9 *Computing time*. How much calculation time does it take to make forecasts?
10 *Explainability of the forecasts from a non-technical point of view*. Are the forecasts logical and can be explained in simple terms? Can the forecasts be traced back to specific input variables or is everything connected?
11 *Fairness*. To what extent can unfortunate choices or decision rules lead to the algorithm unintentionally becoming discriminatory?

This report will look at alternative forecasting methods, what kind of data is required for this and to what extent they could be applied without negating the advantages of the current PMJ, in particular network consistency. Therefore, any alternative algorithms must meet a number of prerequisites:

- The empirical model must be network consistent. The forecast of the output of one network partner must affect the forecast of the inflow of the subsequent network partner.
- It must be possible to predict seven years ahead, i.e. the budget horizon plus the years between the last known data point and the first budget year.
- The forecasts must be explainable from a non-technical point of view. Policymakers want to be able to understand why the forecasts are the way they are. In practice, this means that they must be traceable to specific input variables and that the estimated relationship must contain a certain degree of logic.
- Due to the planning of the budget process, the parameters of the model must be updated annually by mid-November. Because some data is only available at the end of September, this means in practice that the update must take place within a period of approximately six weeks.
- The chosen algorithm must be fair. Choices or decision rules may not unintentionally lead to the algorithm becoming discriminatory in nature.

Alternative methods

The examined techniques originate from the fields of machine learning and econometrics. Although there is a large overlap between the techniques used in econometrics and machine learning, econometrics works more from theory and machine learning is more data-driven. Roughly speaking, the alternative methods fall into four categories: alternative ways of estimating the parameters of the current PMJ, a different specification of (parts of) the model, methods that relate to greater use of the datasets that are used for estimating and testing the parameters of the model and combining methods or samples.

Alternative ways of estimating the parameters of the current PMJ

Linear regression is a simple and therefore frequently used class of algorithms for linear or linearised models. So far, the equations in the PMJ are mostly estimated with ordinary least squares. However, an algorithm that may be interesting for the PMJ is linear regression with elastic net regularization and in particular ridge regression. This method imposes a penalty on excessive complexity (i.e. the number of exogenous variables) of the model. If the data contains any significant problems, such as outliers, poorly measured or correlated exogenous variables, truncated or censored data, and small or skewed samples a modified linear algorithm can be applied. However, often these problems can also be solved in a simpler way.

Other specification of (parts of) the PMJ

If the variable to be forecasted is an amount of some sort, both linear and non-linear regression can be used, such as linear or non-linear time series analysis or survival analysis (non-linear). Time series analysis is widely used for forecasting because it is relatively easy to implement and is integrated in many software packages. Linear time series analysis is already used to a limited extent in the current PMJ. However, the data must meet several conditions. A disadvantage is that time series analyses are mainly suitable for short-term forecasts because time series models tend to revert to the mean of the process in the long term. Other forms of non-linear regression that may be of interest to PMJ are duration data algorithms. In particular, a (semi-) parametric survival analysis of duration data seems promising for those parts of the justice field for which the duration is not known in advance, such as pre-trial detention or indefinite detention in a psychiatric prison hospital.

For the forecasts of certain choices there are algorithms such as discriminant analysis, naive Bayes algorithm or logistic regression. For the PMJ, logistic regression seems to be a logical option: there are many choices within the judicial system. Should a suspect be held in remand custody? Should a suspect be prosecuted and/or tried? What type of sanction should be imposed? These are typical choices that can be predicted with a logistic regression. Nevertheless, there are also limitations. The purpose of the PMJ is to predict seven years ahead. It is difficult to include the time aspect in a logistic regression. Furthermore, logistic regression is applied to microdata. The question is whether the risk of privacy violations outweighs increased insight into the forecasts. Discriminant analysis is a simple, computationally efficient algorithm, especially suitable for small samples with a limited number of exogenous variables. The naive Bayes algorithm is also technically easy, but the results are less intuitive if one has no knowledge of or affinity with probability distributions. This makes both algorithms less useful for the PMJ.

There are also algorithms that can predict both amounts and choices, such as k-nearest neighbours, decision trees, support vector machines and neural networks. These non-parametric algorithms have the advantage that very little assumptions about the data are made in advance. The advantages and disadvantages differ per algorithm. All things considered, k-nearest neighbours and decision trees could be a good addition to the PMJ, where the main disadvantages of not being able to trace back to specific background factors or the absence of the time component, respectively, will have to be weighed against the advantages. Support vector machines and neural networks are less likely candidates mainly because the calculation time of these algorithms is large, and the updating of the models cannot be achieved in a satisfactory manner within the available time (approximately six weeks). Another disadvantage, particularly with neural networks, is that everything is interconnected, and forecasts cannot be explained from a non-technical point of view.

Greater utilization of the dataset

There are several methods which make broader use of the current sample. One way is to improve the validation errors or the standard errors and the confidence intervals of the estimated parameters. By means of bootstrapping or cross-validation, multiple subsets can be drawn from the same sample, with which the same model is estimated each time. These methods are used to compare different theoretical models and/or algorithms with each other in terms of predictive power. Bootstrapping in particular, can be interesting, especially in combination with alternative algorithms. But with a large number of models, algorithms and/or observations, it can be very computationally intensive. Moreover, both methods are somewhat difficult to apply to time series. Also, because the PMJ is usually not assessed solely on predictive power, but on several criteria, including theoretical correctness and explainability from a non-technical point of view, especially with cross-validation the marginal advantage of better predictive criteria and knowledge about the distribution of the parameters does not seem to outweigh the disadvantage of greater computational intensity.

Another way of making broader use of the current sample is to include combinations of exogenous variables in the model instead of individual exogenous variables, for example by means of principal component analysis or factor analysis. The major disadvantage is that the resulting forecasts cannot be traced back to specific background factors and can therefore not be explained from a non-technical point of view. Therefore, the application of principal components analysis or factor analysis is less desirable for PMJ.

Combining methods or sampling

There are several ways in which different forecasts of the same variable can be combined. Both bagging and boosting combine forecasts from the same algorithm but different samples. Bagging, or bootstrap aggregating, could be interesting for the PMJ, because it is relatively easy to implement and the model itself does not become too complex, so that the results are still explainable. Bagging is also an essential part of the random forest algorithm. Random forest is a forest of decision trees, where each decision tree is built on a different bootstrapped sample of observations and/or a different random selection of the exogenous variables. Boosting is less interesting because it requires very high data quality without outliers and noise and it is computationally intensive, meaning that the forecasts cannot be updated within the available time.

Ensemble averaging and stacking allow forecasts from different algorithms to be combined on the same sample. With ensemble averaging, an average is calculated, while with stacking a metamodel is formulated. Ensemble averaging is a promising technique for the PMJ, because it is relatively easy to implement, and different algorithms are often tried out in the test phase anyway. Until now, one model was ultimately chosen based on various criteria, although the differences in prediction quality were often minor. Alternatively, the average of the forecasts from multiple models could be calculated. For example, the inflow into the Public Prosecution Service could be predicted based on the number of suspects recorded by the police, but also by means of a time series analysis. The final forecast then becomes the (weighted) average of the outcomes of both algorithms. Stacking could be an option if the metamodel is not too complicated. But the disadvantage is that it takes a lot of calculation time and requires (relatively) a lot of data.

Conclusion and recommendations

In contrast to econometric models, machine learning models are mainly data-driven and therefore mainly based on correlations and not so much on causal relations. A recent development is the growing attention for causal and explainable machine learning techniques, the so-called 'explainable artificial intelligence' (XAI). This means that the machine learning models and the econometric models are evolving toward each other. This also seems to be the most promising development direction for the PMJ, but XAI is an area of knowledge that is still under development. Given the nature of the data, the purpose of PMJ and the prerequisites, the most promising alternative algorithms are:

- algorithm that imposes a penalty on excessive complexity of the model (linear regression with elastic net regularization);
- analysis of duration data for psychiatric prison orders or pre-trial detention (survival analysis);
- algorithm that assumes that similar characteristics of the exogenous variables lead to comparable values of the endogenous variable (k-nearest neighbours);
- algorithm for choices, such as the type of punishment to be imposed (logistic regression, decision tree);
- broader utilization of the existing data set (bagging of bootstrapped samples);
- combination of multiple decision trees through bagging (random forest);
- combination of the results of different algorithms (ensemble averaging);
- time series analysis for ensemble averaging.

These algorithms largely meet the prerequisites, but sometimes concessions will have to be made. In a follow-up study, several pilots will be carried out with these algorithms to see whether these algorithms actually lead to better forecasting performance.

Het Wetenschappelijk Onderzoek- en Datacentrum (WODC), Kennisinstituut voor de rechtsstaat, is een onafhankelijk kennisinstituut dat valt onder het ministerie van Justitie en Veiligheid. Het WODC draagt bij aan behoud en verbetering van de rechtsstaat via het (laten) uitvoeren van kwalitatief hoog wetenschappelijk onderzoek. En door het aanbieden van gevraagde en ongevraagde kennis, verbeterpunten en (waar mogelijk) denkrichtingen.

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