Why are Italian trials taking so long? A process mining approach

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Abstract

The duration of processes is a critical aspect in the Italian judicial system. In this paper we introduce an original approach based on process mining and machine learning techniques to analyse temporal aspects of processes represented as a Finite State Machine. We analyse both the variants of trials execution in terms of possible sequences of states and their duration and the impact of single events on their completion time. A case study based on civil cases registries of the Court of Appeal of Milan is discussed.

Keywords

Judicial Systems, Process Mining, Trials temporal analysis

1. Introduction

Judicial systems are responsible for supporting the functioning of the economy by ensuring the protection of property rights and the enforcement of contracts. Empirical studies show that the inefficiency of justice, due to the length of proceedings and the lack of "legal certainty", depresses the economy and contributes to creating a climate of uncertainty and distrust which negatively affects the entrepreneurial and innovative capacity of a country. More specifically, inefficient civil justice has a negative impact on the cost structure of firms, on the allocation and cost of credit, on the birth rate of firms, their ability to enter markets and competitiveness, on the size of production units, on domestic investments and on the ability to attract foreign investments [1]. It is estimated that delays and inefficiencies in justice generate a loss of over 16 billion euros, equal to 1 per cent of GDP, consequently slowing growth [2].

Understanding the causes of these delays is crucial for improving the efficiency and efficacy of civil justice systems. In this work, we aim to investigate the reasons behind the slow functioning of civil justice by analysing data extracted from the log of the Finite State Machine (FSM) that memorises all events related to a civil trial.

The FSM is a valuable resource, as it provides detailed insights into the various stages of a civil process, allowing us to track the progression of cases and identify bottlenecks or inefficiencies. By leveraging a comprehensive dataset from the Court of Appeal of Milan, we examine the key factors contributing to the slow pace of civil justice. The aim of the research is to contribute to the ongoing efforts to increase the efficiency of civil justice, in particular considering reduction of duration of trials.

In Section 2 we illustrate the state of the art. Section 3 discusses the considered scenario. The proposed analyses methods and initial results are illustrated in Section 4.

2. Related work

Judicial systems in recent years have been more and more supported by information systems that allow storing registries of events occurring during processes and linking them to the official documents and acts related to them.

The number of trials being recorded in the Italian Civil digital judicial information system (SICID) has increased, reaching 100% of cases in the Court and Court of Appeal of several cities including Milan. The increased use of information systems allowed analysing more and more in depth some Key Performance indicators, such as the Disposition Time (DT) and the Clearance Rate (CR) of cases. Several efforts are being conducted at the European level in the direction of monitoring the performance not only of terminated cases, but also of ongoing trials [3]. Recent data report that Italian courts, while reducing backlogs, have still much longer durations of trials than in other European countries[1].

As analysed by some authors [4, 5], it is important not only to analyse the global behaviour of processes, but also their critical situations, and the application of process mining techniques is advocated. Process mining [6] allows analysing a process through the steps of

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[1]https://www.coe.int/en/web/cepej/special-file\protect\discretionary{\char\hyphenchar\font}{}{}report-european-judicial-systems-cepej-evaluation-report-2022-evaluation-cycle-2020-d

data extraction, data preparation, process discovery, conformance and compliance checking, and performance analysis. Recently, AI-augmented process mining is being investigated. In [7] waiting times are investigated, classifying different types of causes of delays such as batching or resource contention, and proposing methods to identify them on the basis of mining activity transitions. In the case of trials, other typical events that would also be necessary to investigate are blocking events and events linked to waiting times inherent to the normal execution of a process (e.g., waiting for the date fixed for the hearing).

Process mining has been applied to judicial systems in Brazilian courts [4] to derive process maps which are used to identify slow transitions and activity bottlenecks and to analyse the times of processes on the basis of different analysis dimensions, e.g., comparing paper-based and digital processes. In [5], process mining based on causality graphs is performed considering outlier cases, which allows identifying the main events that may delay the processes. However, this type of analysis does not allow to identify causes of delays that are not linked to pairs of events and further research is needed to analyse the impact of events in general. Other recent directions in applying AI techniques to trials, are presented in [8], where different deep learning techniques are applied to predict the duration of a phase. However, in these analyses, the sequences of events are not being considered and the focus is on a single phase. More general methods are needed, taking into consideration the different possible variants of processes and sequences of events.

3. Scenario

3.1. Italian digital civil judicial system

The Italian information system for civil cases (SICID) is based on a FSM and it supports the activities by the Chancellor and the decisions of judges recording of events as exemplified in Fig. 1, linking them to the relevant documents and acts. For each of them, the date of the event is stored, together its recording date, the type of event, and the states before and after the event. Privacy is of utmost importance when dealing with individuals involved in civil cases; as such, the data is provided in an anonymized form. This information is the basis for the analyses described in the following of the paper, which is focusing on temporal analyses of trials durations.

The analyses illustrated in this paper are based on the analysis of more than 15,000 defined civil cases in the last five years within the Court of Appeal of Milan. The processes under consideration pertain Ordinary second degree procedures (4O rite), for four sections, considering Litigations (*Contenzioso*).

NUM_RUOLO	CTIPSE	CCODST	CSTAPR	CDESCR	CCDOEV	DESCR_EV	DATAEV	DATARE
1/2018		AS		ATTESA ASSEGNAZIONE SEZIONE	IA	ISCRIZIONE RUOLO GENERALE	2018-01-02	2018-02-09
1/2018		AS	AS	ATTESA ASSEGNAZIONE SEZIONE	RP	RICHIESTA FASCICOLO PRIMO GRADO	2018-02-09	2018-02-09
1/2018	04	GC	AS	ATTESA DESIGNAZIONE GIUDICE REL./COLLEGIO	AS	ASSEGNAZIONE A SEZIONE	2018-02-16	2018-02-16
1/2018	04	GC	GC	ATTESA DESIGNAZIONE GIUDICE REL./COLLEGIO	W1	ALLEGATO FASCICOLO DI PRIMO GRADO	2018-02-16	2018-02-16
1/2018	04	UT	GC	ATTESA ESITO UDIENZA TRATTAZIONE (Art. 350)	0F	DESIGNAZIONE GIUDICE E FISSAZIONE PRIMA UDIENZA	2018-02-19	2018-02-19
1/2018	04	UT	UT	ATTESA ESITO UDIENZA TRATTAZIONE (Art. 350)	B2	ACQUISIZIONE FASCICOLO	2018-03-27	2018-03-27
1/2018	04	UT	UT	ATTESA ESITO UDIENZA TRATTAZIONE (Art. 350)	CP	COSTITUZIONE PARTI	2018-05-14	2018-05-14
1/2018	04	UT	UT	ATTESA ESITO UDIENZA TRATTAZIONE (Art. 350)	J1	DEPOSITO ATTO NON CODIFICATO	2018-06-12	2018-06-12
1/2018	04	PC	UT	ATTESA ESITO UDIENZA DI PRECISAZIONE CONCLUSIONI (Art. 352)	YB	RINVIO ALL'UDIENZA DI PRECISAZIONE CONCLUSIONI (art.352 cpc)	2018-06-14	2018-06-14

Figure 1: Sample registry

3.2. Data preparation

The data pertaining to the progression of a civil process is stored within an Oracle database. Before starting the analysis, all data must be imported into our database. The raw data may include inconsistencies, errors, or missing values. To clean the data, we will identify "impossible values", such as events with future dates or those too far in the past (out of the timeframe covered by the given logged data), and incomplete data, such as civil processes missing records of essential steps. Data identified during this process, which constitutes less than one per cent of the total, will be removed and disregarded. We will also eliminate data related to civil procedures that were opened and closed on the same day, as these do not represent complete civil processes and could impact the evaluation altering the data calculation.

Data analysis will involve clustering the data based on the tribunal section number and the subject matter of the process. This is because different sections and matters necessitate distinct procedures, and as such, varying events and timeframes are expected.

The final stage of data preparation involves calculating additional variables, such as the duration between events, the total duration of a case, and the duration of different case phases.

4. Temporal analyses

In the following, we present different types of analysis. First, we concentrate in analysing the different phases of a process, analysing their states and their duration.

We then focus on a finer perspective of the analysis, analysing events within a single state in the direction of identifying the events which have a larger impact of their duration.

4.1. Variant analysis with process mining

The analysis of variants of a legal process using process mining methodologies, such as Apromore[2], is a fundamental practice to understand and improve efficiency and effectiveness of legal processes. Process mining is a data-driven technique that allows examining, analysing, and optimising processes using information extracted from event logs.

Variants of a judicial process refer to the different paths that a case can follow during its evolution, which includes steps such as assignment to a section, appointment of the judge, waiting for hearings or documents, and decision phases. Analysing these variants can help identify recurring patterns, inefficiencies, and areas for improvement in the justice system.

Using Apromore, an effective open-source process mining platform, one can analyse in depth the variants of a legal process, the process variants can be analysed and, based on the information gained from variant and performance analysis, changes can be proposed to the execution of juridical processes to improve efficiency, reduce waiting times and increase user satisfaction.

As a first type of analysis, we focus on states and the transitions between states, ignoring internal events within states. By examining the sequences of states rather than individual events, the complexity arising from the multitude of events and their potential combinations is avoided. In this way, a clearer and more comprehensible representation of the process is achieved and the main variants can be identified.

From the analysis of the variants, three main paths emerge that a case can follow, covering 66% of the cases. The first variant, which accounts for about 48% of cases, corresponds to the base variant of the ordinary second degree process, which includes all the typical stages of such process, from its initial registration to the publication of the judgement. The second and third variants, with frequencies around 10% and 8% respectively, represent shortened paths, having respectively one and two states less than the main variant. These shortened routes may be the result of simplified legal procedures, agreements between the parties or other special circumstances. The rest of the variants, although less frequent, represent more particular cases that can offer useful information on specific situations or exceptions to the standard. It is also possible to compare processes which have a similar sequence of events, in terms of their execution time, as well as to analyse their individual phases, and identify both general critical issues and the most critical phases.

[2]https://apromore.com/

4.2. Analysis of the impact of events

After analysing each state of the process, we can proceed to investigate the most critical states more in detail to understand which events have a greater influence on the total time duration of a state.

Measuring the impact of a single event on the duration of a state is challenging. Since the interdependencies between different events are not known in advance, the data cannot be treated as a time series because the duration of an event cannot simply be calculated as the date of the following event minus the date of the event itself. To overcome these challenges, we use machine learning models, following [9], to create a regression model that predicts the time of a state based on the presence or absence of specific events[3].

The final aim of this model is to interpret the covariates in order to understand which events have a significant impact on the state.

To develop the regression models, we tested a range of machine learning techniques. The dataset includes the events that occur in a state and the corresponding total time duration of the state. The covariates are represented by the presence or absence of the events, while the outcome variable is the duration of the state. We performed analyses with decision trees, random forests, and gradient boosting algorithms to train different models, and we use k-fold cross-validation to evaluate the performance of each model. Once a model predicts the outcome accurately, we then interpret the covariates to understand which events are more important in terms of total duration of the state.

Notice that simple feature interpretation directly from the predictions of the model is not enough to clarify how the covariates affect the outcome. Indeed, even if you examine a specific scenario where the number of legal processes is low, the number of covariates (the events in the state) is still high; hence it is too complex to qualitatively understand the interaction between the events. Spotting the dependencies between the events is fundamental to evaluate which feature has a significant impact on the outcome of the prediction. For this reason, we use Shapley values and permutation importance methods to interpret the covariates in the model [10]. Shapley values are a game theoretic approach to assign importance scores to the features in a model. It helps us understand how each event contributes to the duration of the state. By calculating the Shapley values of each event, we can identify the events that have the most significant impact on the total time of the state.

Permutation importance, on the other hand, measures the importance of each feature by randomly permuting the values of that feature and calculating the resulting decrease in the performance of the model. By comparing

[3]All the models have been developed via Python 3.11

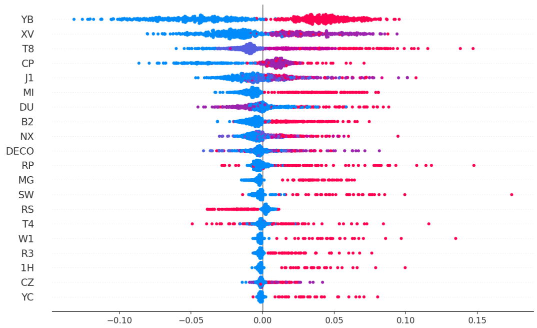

Figure 2: Graphical representation of the Shapley values of a Random Forest model for this for the state "UT" (Waiting for the first hearing

the decrease in performance of the model when each feature is permuted, we can determine the features that have the most significant impact on the outcome.

For example, Fig. 4.2 shows preliminary results for a specific case; the events are sorted by importance and the coloured dots of the image are associated to each prediction of the legal processes. Blue dots represent the processes where the event is absent; violet and red dots (darker dots) represent the processes where the event is present once and more than once. The dots on the right side of the x-axis represent the predictions where the event influences positively the outcome; vice versa for the left side of the x-axis.

We can observe that in general red dots are on the right side of the x-axis, meaning that the presence of an event influences positively the total duration of the state; this was also expected a priori. Moreover, we can examine which events are more important and take into consideration only the flexible and optimisable ones. Interesting events in the state of Waiting for the first hearing are "XV" and "MI". The first one represents the event of a lawyer who asks the permission to analyse the file of the process; the second one describes a postponement of the court hearing asked by one of the parties. Both are important in terms of Shapley values and both are events that can be considered for optimisation.

As a result, using machine learning models and techniques such as Shapley values and permutation importance, we gain a deeper understanding of how the events contribute to the duration of trials. By creating a regression model, we can predict the time of a state based on the presence or absence of specific events.

4.3. Predictive techniques for process duration

In addition to analyzing single state, our research work focuses on creating predictions models for the duration of an ongoing process or even before it begins, based on historical data and information extracted from variant analysis. These models can be used to predict both the states that will be traversed during the process and the overall duration of the case. To this purpose, we can use timeline models, such as Markov chains [11] or RNN models (Recurrent Neural Networks) [12]. These models can learn the transition probabilities between states and predict the most likely sequence of future states, considering the process variants observed in historical data. To predict the overall duration of a process, it is possible to use regression models, such as linear regression, tree models such as Random Forest [13] and XGBoost [14], or deep learning models such as artificial neural networks [15]. These models can be trained on numerical and categorical variables, such as process type, process variant, start year and month, and other relevant information, to estimate the duration of the process based on the specific characteristics of the case. For prediction of duration of cases, we focus on Markov Chain Models, which have the advantage of being more easily interpretale wrt other approaches. Prediction of durations of states is discussed in Sect. 4.3.2.

4.3.1. The Markov Chain Model for juridical process analysis and prediction

The Markov chain is a statistical model used to analyse the transition probability of a system of discrete states over time. The Markov model is based on a transition matrix, which describes the probability of transition from one state to another. For example, suppose having a judicial process with three discrete states: the state of filing of a case, the state of the first hearing, and the state of the judgement.

In this case, for instance, the transition in the transition matrix indicate that the probability of moving from the state of filing a case to the state of the first hearing is 60%, while the probability of moving from the state of the first hearing to the judgement is 20%.

In general, the implementation of a Markov model for predicting the path of a legal process involves several stages. The first step is to define the discrete states of the system. In the case analysed, the system is characterised by a total of 48 possible states. Next, data related to past judicial processes needs to be collected to estimate the chances of transition between states. Finally, once the transition matrix has been defined, it can be used to predict the future path of the judicial process.

The use of Hidden Markov Model (HMM) [16] can

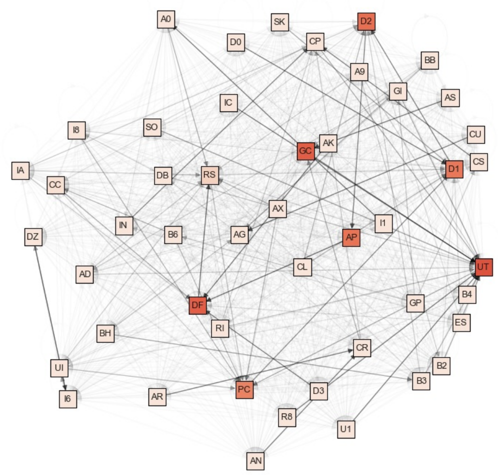

Figure 3: Graphical representation of the transition matrix for the Court case study

be an interesting alternative for predicting the path of a judicial process compared to the simple Markov model. In an HMM, an additional element is introduced with respect to the Markov model, namely observation. In other words, each state can be associated with an observation that depends on the characteristics of the judicial process in that state. For example, for the judicial process, the observation could be the duration of the trial up to that point. The main advantage of using an HMM over the simple Markov model is that, thanks to observations, it is also possible to capture the uncertainty associated with transitions between states. In other words, the probability of transition from one state to another also depends on the observation associated with the current state, which makes the model more accurate.

In Fig. 3, a graphical representation of the transition matrix in the case study is provided. The nodes of the graph represent the 48 states identified in the logs. The colour intensity of each node depends on the number of times the state is traversed, while the opacity of the arcs depends on the probability of moving from the starting node to the destination node.

4.3.2. Approaches to predicting duration of legal process states

With regard to predicting the duration of individual process states and the overall duration of the process, there are several approaches that can be used independently or in combination with the Markov or HMM model. A common approach is to use historical data to estimate the probability distribution of the duration of each process state, for example by using statistical analysis techniques such as regression or survival analysis. These probability distributions can then be used within the Markov or HMM model to estimate the overall duration of the process. Another approach is to use machine learning techniques to predict the duration of individual process states. One of the main features of this approach is its flexibility. Machine learning models can be tailored to the specific needs of the judicial process and can capture non-linear relationships between variables that influence its duration. In addition, machine learning models can also be used when data is missing or incomplete.

All implemented models are developed using the Python programming language. The Scikit-learn machine learning library is utilised for the development of all deep learning models, the simple Markov chain models are developed from scratch, and the HMM model developed using the hmmlearn library. A first implementation has been carried out using the XGBoost model. The dataset used consists of more than 15.000 defined processes and has been divided randomly into training set and validation set according to an 80%/20% ratio. Input variables include the year and month of registration of the trial, the section and judge to whom it was assigned, the role, juridical matter and juridical object. More variables are available and will be added in the future. The current model generates predictions with a mean absolute error of 3.85 months. The analysis of the residuals shows some heteroskedasticity, probably due to the omission of independent variables, scalar effects and nonlinear relationships not properly considered, and it will be addressed in future developments.

4.3.3. Benefits of predictive and simulation models in juridical process management

A predictive and simulation models of legal processes can have a significant impact on the organisation of a court, contributing to the efficient management of resources and achieving the government's goals of reducing timeframes.

Firstly, an accurate predictive model of the duration of legal processes and the states that will be encountered can help distribute the workload among different sections and judges. By knowing the expected duration and complexity of various cases, court officials can assign cases equitably, avoiding overloading and ensuring that each judge has a manageable workload.

Secondly, predictive models can help identify bottlenecks and inefficiencies in the judicial system. By analysing process variations and their duration, court officials can identify the process stages that require more time and resources, and implement strategies to improve efficiency in these critical areas. Additionally, process simulation models can be used to evaluate the impact of possible procedural or regulatory changes. By using a simulation model, officials can predict the effects of such changes and make informed decisions on how to implement them as effectively and efficiently as possible.

In addition to the aforementioned benefits, the use of predictive models and simulations can also improve communication and transparency between judges, chancellors, lawyers, and parties involved in legal processes, helping reduce uncertainty regarding timing and procedures. Finally, the implementation of these models can promote a culture of continuous improvement within the court. With regular analysis of process data and model updates to reflect changes in the judicial system, courts can adapt to new challenges and continue to improve the efficiency and effectiveness of their operations.

5. Concluding remarks

The paper has presented an innovative approach to analyse judicial cases and the impact of events on their completion time. A temporal analysis of states has been performed using process mining techniques and a fine-grained analysis of states is proposed based on machine learning techniques. Predictions of duration of cases are performed using HMM. Extracting this information is essential to understand the dynamics and peculiarities of the justice system. Knowing the most common process variants and their frequencies can help identify trends, inefficiencies and opportunities for improvement. In addition, this information can be used as a basis for further analyses of critical events, and to develop strategies aimed at reducing waiting times and improving the efficiency of the justice system.

Ongoing work includes a deeper analysis on the different possible types of events in judicial cases and prediction models for ongoing processes, in order to identify possible critical aspects in their outcome.

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