Legal Reasoning and Big Data: Opportunities and Challenges

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Abstract. The main underlying assumption of traditional legal knowledge representation and reasoning is that knowledge and data are both available in main memory. However, in the era of big data, where large amounts of data are generated daily, an increasing range of scientific disciplines, as well as business and human activities, are becoming data-driven. This paper discusses new opportunities and potential applications of legal reasoning involving big data as well as the technical challenges associated with the main concepts of the big data landscape, namely volume, velocity, variety and veracity. Future research directions based on the identified challenges are also proposed.

Keywords: Legal Reasoning · Big Data · Large-Scale Reasoning.

1 Introduction

Since the emergence of computational knowledge representation and reasoning (KR), the domain of law has been a prime focus of attention as it is a rich domain full of explicit and implicit representation phenomena. From early Prolog-based approaches [40, 42] to elaborate logic-based mechanisms for dealing with, among others, notions of defeasibility, obligation and permission, the legal domain has been an inspiration for generations of KR researchers [1, 14, 26, 43].

Knowledge representation has been used to provide formal accounts of legal provisions and regulations, while reasoning has been used to facilitate legal decision support and compliance checking. Despite the variety of approaches used, they all share a common feature: the focus has always been on capturing elaborate knowledge phenomena while the data has always been small. As a consequence, one underlying assumption has been that all knowledge and data are available in main memory. This assumption has been reasonable until recently, but can be questioned with the emergence of *big data*. We now live in an era where unprecedented amounts of data become available through organisations, sensor networks and social media. An increasing range of scientific disciplines, as well as business and human activities, are becoming data-driven.

Since legislation is at the basis of and regulates our everyday life and societies, many examples of big data such as medical records in eHealth or financial data, must comply with, and are thus highly dependent on, specific norms. Huge amounts of financial transactions must follow strict regulations; complex food supply chains with myriads of sensor-based tracking data must comply with food regulations in various countries; many Web-based activities must still comply with national or international laws.

Industries are feeling increasingly overwhelmed with the expanding set of legislation and case law available in recent years, as a consequence of the global financial crisis, among others. Consider, for example, the European Union active legislation, which was estimated to be 170,000 pages long in 2005 and is expected to reach 351,000 pages by 2020 assuming that legislation trends continue at the same rate [31]. As the law becomes more complex, conflicting and ever-changing, more advanced methodologies are required for analysing, representing and reasoning on legal knowledge.

As a result, regulative technology (RegTech) and, in particular, Fintech, i.e. RegTech applied to the financial domain, has recently received a lot of attention due to the proliferation of legislative documents as well as the increase of the associated sanctions: since 2008, the banking industry alone has received more than $300 billion in the form of such penalties from public institutions [29].

The term "big data" is usually associated with machine learning, which is concerned with discovering hidden patterns in data, deriving new insights and making predictions. In recent years, the application of machine learning in the legal domain has received significant attention [24, 28, 34]. However, we argue that particularly in law there is also a need for symbolic approaches. Legal provisions and regulations are considered as being formal and legal decision making requires clear references to them. Stated another way, in the legal domain there is also a need for *explainable artificial intelligence*, as it has always been done in legal reasoning.

So what are the implications of this big data era on legal reasoning? On the one hand, as already explained above, a combination of legal reasoning with big data opens up new opportunities to provide legal decision support and compliance checking in an enhanced set of applications. On the other hand, there are new technical challenges that need to be addressed when faced with big data. Big data questions the main underlying assumption of traditional legal KR that knowledge and data is available in main memory; indeed, this data does deserve specific attention:

- When the amount of data is huge, one cannot assume that all data is available in main memory (Data Volume)

- In complex applications, such as food supply chains, the heterogeneity of data cannot be neglected (Data Variety)
- In applications where one wishes to perform decision making close to the time data is generated, the dynamicity of data needs to be taken into account (Data Velocity)
- Data coming from various sources should be examined on the degree of trust one has on the source of each dataset (Data Veracity)

The aim of this paper is to present a collection of potential applications of legal reasoning involving big data, and to work out associated technical challenges that need to be addressed. In doing so, the paper aims to stimulate the evolution of the area of legal reasoning so that it becomes more relevant in the new data-driven era.

The paper is organised as follows. Section 2 provides an overview of previous legal reasoning research. Section 3 collects a number of potential applications requiring the combination of legal reasoning and big data. Section 4 provides a description of technical challenges arising from these applications. Finally, Section 5 presents a summary of findings and future research themes and Section 6 concludes.

2 State of the Art – Legal Reasoning

Research on the confluence of AI and law has been active for more than four decades. We refer the interested reader to detailed accounts of such research in [38, 8, 37]. In this section, the focus is only on the various approaches for legal knowledge representation and reasoning.

Early attempts at realising normative reasoning involved representing legislation in the form of Horn logic programs, such as Sergot et al.'s seminal work on the British Nationality Act [42]. However, monotonicity and the treatment of negation in pure Prolog proved problematic. Extensions that support negation as failure and negated conditions solve some issues but raise others, such as the cases of double negation and counterfactual conditionals (e.g. "if it didn't rain"). Also, introducing new exceptions to existing legislation would mean rewriting the whole logic program to take such exceptions into account. Hence, Prolog and its variants prove useful only in representing self-contained and stable legislation [25], but even so, they can only model the questions that need to be answered in a legal debate, not how they are to be answered [8].

Following the advent of the Semantic Web and the introduction of the OWL family of languages, several research efforts focused on examining whether description logics are a suitable candidate for representing and reasoning about legislation. A prime example is HARNESS [52] (also known as OWL Judge [53]), which shows that well established sound and decidable DL reasoners such as Pellet can be exploited for normative reasoning, if, however, a significant compromise in terms of expressiveness is made. The most important issue is that relationships can only be expressed between concepts and not between individuals: for instance, as exemplified in [52], if we have statements expressing the facts that a donor owns a copyright donation and that a donor retains some rights, there is no way to express (in pure OWL) that the donor in both cases is the same individual. This can be expressed via rules (e.g. written in SWRL); however, to retain decidability these rules must be restricted to a so-called DL-safe subset [35].

A common issue that arises when using classical or description logics in normative reasoning is the fact that they are monotonic: logical consequences cannot be retracted, once entailed. This is in contrast to the nature of law, where legal consequences have to adapt in light of new evidence and conflicts between different regulations must be accounted for and resolved. Therefore, it is natural to employ non-monotonic logic for the purposes of normative reasoning. The Defeasible Logic framework [5] has been applied in a normative reasoning setting due to its simplicity and flexibility and the fact that several efficient implementations exist [4, 27]. In the Defeasible Logic framework, rules can either behave in the classical sense (*strict*), they can be defeated by contrary evidence (*defeasible*), or they can be used only to prevent conclusions (*defeaters*).

The notions of permission and obligation are inherent in normative reasoning but are not explicitly defined in traditional logic systems; deontic logic was introduced to serve this purpose. As formalised in [18], permission and obligation are represented by modal operators and are connected to each other through axioms and inference rules. While there has been some philosophical criticism on deontic logic due to its admission of several paradoxes (e.g. the gentle murderer), deontic modalities have been introduced to various logics to make them more suitable for normative reasoning. For instance, [17] and [16] show how the aforementioned Defeasible Logic framework can be extended to model beliefs, intentions, obligations and permissions, while [41] uses a combination of deontic logic and the notions of action and agents to be able to derive all possible normative positions (e.g. right, duty, privilege) and assist in policy and contract negotiation.

The aforementioned approaches are more suited to legal systems that are primarily based on civil law, due to their rule-based nature and the fact they focus on conflicts arising from conflicting norms and not from interpretation [9]. On the other hand, common law places precedents at the centre of legal reasoning, which makes case-based approaches, such as HYPO [6], CATO [3] and GREBE [10] more applicable. CATO replaces dimensions, which are used to determine case commonality in HYPO, with boolean factors organised in a hierarchy. GREBE is a rule/case hybrid, since reasoning relies on any combination of rules modelling legislation and cases represented using semantic networks. As noted in [8], using dimensions or factors to determine legal consequences is relatively tractable, but the initial step of extracting these dimensions or factors from case facts is deeply problematic.

Regardless of the legal system applied, legal reasoning at its core is a process of argumentation, with opposing sides attempting to justify their own interpretation, with appeals to precedent, principle, policy and purpose, as well as the construction of and attack on arguments [37]. AI and law research has addressed this with models that are based on Dung's [13] influential work on argumentation frameworks, such as Carneades [15], a model and a system for constructing and evaluating arguments that has been applied in a legal context. Using Carneades, one can apply pre-specified argument schemes that rely on established proof standards such as "clear and convincing evidence" or "beyond reasonable doubt". ASPIC+ [36] takes a more generic approach, providing a means of producing argumentation frameworks tailored to different needs in terms of the structure of arguments, the nature of attacks and the use of preferences. However, neither Carneades nor any ASPIC+ framework can be used as-is for legal reasoning: they need to be instantiated using a logic language. For instance, versions of Carneades have used Constraint Handling Rules to represent argumentation schemes, while any ASPIC+ framework can be instantiated using a language that can model strict and defeasible rules, such as those in the aforementioned Defeasible Logic framework.

It is worth mentioning that the recent proliferation of machine learning research has led to several data-centric approaches, differentiated in [11] based on whether they are oriented towards documents, cases or corpora. The latter two are more related to legal reasoning, using predictive analytics based on either past cases or collections of legal texts. A recent notable example is [2], where binary classifiers are applied on documents of cases tried at the European Court of Human Rights in order to predict judgment on future cases based on similarity.

Legal reasoning is a complex reasoning task, as illustrated by the abovementioned approaches, with applicability depending on the volume of data. Related work on large scale semantic reasoning includes several approaches applied on different logic formalisms, often restricting expressiveness in order to increase performance. For simpler, monotonic knowledge representation formalisms such as RDF/S systems efficient large-scale implementations exist. For instance, DynamiTE [50], which supports the ρdf fragment of RDF, can be used for reasoning over 1 billion triples. The Hadoop based WebPIE system [49] can be used for reasoning over 100 billion triples. The VLog system [48] supports the more expressive OWL RL language and can be used for reasoning over 0.5 billion triples.

The aforementioned approaches can be used only for simple legal reasoning tasks, since they do not support non-monotonic reasoning. Related work on parallel argumentation reasoning presented in [12] can be used for reasoning over 8400 arguments, thus it is not an approach suitable for big data. Large scale non-monotonic reasoning applied on the Defeasible Logic framework has been achieved in [46] for rules with a single variable and extended to support stratified rule sets [47], also including negative subgoals [44], as well as over well-founded semantics [45] scaling up to 1 billions facts. This line of work can potentially form the basis of a practical, large scale, legal reasoning system.

3 Case Studies for Large-Scale Legal Reasoning

In this section we provide a range of actual and potential use cases that require legal reasoning over large amounts of data. This collection is not meant to be exhaustive, rather indicative for recognising opportunities and identifying related technical challenges.

3.1 FDA Adverse Event Reporting System

A decision support system for the US Food and Drug Administration (FDA) Adverse Event Reporting System (FAERS) is an application of rule-based legal reasoning [39]. The relevant regulations specify the records and reports concerning adverse drug experiences on marketed prescription drugs for human use without approved new drug applications. For example, there are requirements regarding the reporting of patient age and suspect medical product name, among others. In addition, definitions of various adverse drug experiences are included. The aim of the decision support system is to determine whether there is compliance or non-compliance with these reporting requirements.

The sample database used in [39] covers only the first quarter of 2014 and contains over 3 million records. Experimental results demonstrate that an online system checking for compliance of a new record with FDA reporting regulations is viable. On the other hand, the approach reaches its limits when data over longer periods of time need to be audited.

3.2 Financial Transactions

A source of huge amounts of data is obviously the financial domain, in which millions of transactions take place every single day. At the same time, it is a domain in which many legislations apply regarding, among others, taxation, anti money laundering, consumer rights and data protection. While data mining is being used in the financial domain, it is arguably an area that would benefit from legal reasoning directly related to relevant legislation. In simple cases, this would entail checking for and ensuring compliance with reporting requirements, in use cases similar in principle to the FDA use case above. However, more complex scenarios could involve traversing across financial transaction databases to check for potential violations of legislations, possibly using a combination of legal reasoning and data mining techniques.

3.3 Building Applications and Geodata

Building applications and property/site development are covered by a variety of local and national laws and regulations. To develop and assess relevant applications, it may be necessary to consider the legal requirements in conjunction with geodata relating to morphology of the site and its surroundings, use of space and so on. For instance, it may be necessary to first make a decision about where to build based on regulations and then include suitability of morphology into consideration, or vice-versa. In addition, the built environment is increasingly considered in conjunction with policies to improve public health, for instance. Hence, there is further scope to combine legal reasoning over big data with other types of artificial intelligence (AI), such as AI planning.

Such applications require a semantic representation of spatial information using Semantic Web standards as discussed, for example, in [7, 22] and the integration of such information with legal information as presented in Section 2. Work towards this direction of research, combining geographic information and multi-criteria decision support methods that are represented using ontologies and SWRL rules, is presented in [23]. However, integration of geographic information using semantic technologies is still an open problem, as is determining a rich non-monotonic legal rule representation applied on big data.

3.4 Food Supply Chains

Food supply chains have become international, yet there is an abundance of local laws governing the constitution and distribution of food. In addition, technology is increasingly employed to record information about production and processing sites, as well as to track the provenance and distribution of food components across food supply chains using sensors within an Internet of Things infrastructure. The use of such data can provide information about compliance of food chains as well as identification of risks around outbreaks of diseases, enabling recall and warning calls to satisfy legal obligations.

3.5 Legal Impact Analysis

One of the envisioned advantages of logic-based representations of legal knowledge has been their ability to provide explanations, as well as use these to identify potential problems for proposed changes to laws. To a certain extent, these issues can be addressed by existing legal knowledge representation, in principle. However, there is scope for fundamental research seeking to analyse the impact of legal change. One direction would be to assess the impact of particular changes, exploring, for instance the following questions:

- How would changes in speed limits affect congestion and air quality in cities?
- What are the socio-economic effects of revoking the licence of Uber?
- How would prohibition of Diesel vehicles or the promotion of electric vehicles affect air quality in a city?
- What are the economic effects of altering the taxation treatment of Airbnb earnings?

The questions, of course, can be asked in the opposite direction:

- What changes to speed limits could deliver a smoother traffic flow in a city or region?
- What changes to traffic regulation would keep air pollution under the legal upper limit?
- What changes to the regulations about vehicle use in cities can address air quality concerns?
- What changes to the taxation treatment of Airbnb listings could increase tax revenue and economic activity?

3.6 Streams of Case Data

Case law relies on legal cases being handled by courts. While the traditional approach would be to wait until cases find their way in relevant literature or commentary, a modern approach might involve cases becoming available to be used "in real time", that is, close to the time a ruling is made. This scenario may require dynamic types of reasoning, close to stream reasoning. Such reasoning might be employed, for example, to decide whether a case is standard or landmark, the latter being a case likely to influence future ruling related to the particular case.

4 Challenges of Large-Scale Legal Reasoning

4.1 Volume

Traditional legal reasoning has been focused on storing and processing data in main memory over a single processor. This approach is indeed applicable to small legal documents. However, there is a limit on how many records an in-memory system can hold. In addition, utilising a single processor can lead to excessive processing time. Thus, recent advances in mass parallelisation could potentially speed-up the process.

Recent work [21] indicates that FAERS data can be processed record by record, namely querying the database and performing reasoning for each record separately. Experimental evaluation shows that this approach can evaluate each record within seconds. However, for 3 millions of records this approach requires an estimated time of 8 hours. Given the fact that FAERS data that is readily available is already 10 times larger compared to the ones processed in [21], batch processing would already require days. A record by record processing approach cannot be guaranteed for any given application. Thus, in other applications where all records need to be loaded and processed together, main memory would be a hard constraint considering applicability.

The aforementioned limitations related to memory and processing time are due to the large volumes of legal data that are required for effective reasoning. The challenge is to investigate techniques that can be applied to legal reasoning systems in order to allow them to handle large data volumes, such as mass parallelisation, discussed in Section 5.1.

4.2 Velocity

Financial transactions could potentially require real-time monitoring of day-to-day activity. Such functionality would depend on processing large amounts of transactions within seconds. For cases where reasoning needs to take place during a short window of time, close to the time that events take place, batch reasoning is no longer a viable solution. A prominent challenge in this situation is the efficient combination of streaming data with existing legal knowledge (e.g. applicable laws and past cases), essentially updating the latter. Recent advances in stream reasoning could provide a solution to this challenge, as further analysed in Section 5.2.

4.3 Variety

One of the main challenges in large-scale legal reasoning could be the integration of data coming from disparate sources. Each source could publish data in any possible format, ranging from images of scanned pages to machine processable files. However, use cases such as building applications and food supply chains would require the combination of data generated by sources that have little or no coordination among them. Thus, the first challenge is to translate all available data into machine processable data that can be readily stored and retrieved.

Once this data transformation is achieved managing data that are stored in different formats (e.g. plain text, JSON, XML, RDF) would complicate legal reasoning as all data would need to be translated into a single format in order to have a uniform set of facts. Thus, in order to tackle data variety, all available data would need to be stored in a uniform format that would allow automated translation into facts of the chosen legal reasoning framework.

4.4 Veracity

Building applications and use cases for food supply chains might require novel solutions in terms of veracity for data that is either inaccurate or of poor quality. Such data could originate from incomplete or improperly filed archives, while others could be given by third-party sources that are not as trustworthy as organisations that curate their data. Thus, there are issues that need to be considered, including provenance, namely the source of each dataset.

However, even for trusted sources, some form of data curation might still be required in order to improve data quality. In the case of noisy data, advanced techniques would be required in order to retain only the vital parts within the given dataset. Therefore, depending of the nature of the source and the quality of the available data, different reasoning methods would be applicable.

4.5 Analytics

The use cases on legal impact analysis discussed in Section 3.5 would require a combination of reasoning and analytic techniques applied on a large scale. The challenge here is to determine which analytic techniques would prove more suitable to investigate legal impact and the ways these can be combined with legal reasoning.

In some cases, it may make more sense to use analytics to uncover correlations that can inform legal reasoning systems, while in others legal reasoning can play the primary role of determining impactful factors which can then be used as a basis for impact analysis. An indicative discussion of hybrid approaches that combine legal reasoning with optimisation and simulation is provided in Section 5.5.

5 Future Research Directions

5.1 Mass Parallelisation

It has been shown in literature [45, 47, 49] that mass parallelisation can be applied to various types of reasoning. Both supercomputers (e.g. a single large machine with hundreds of processors and a large shared main memory) and distributed settings (e.g. a large number of combined commodity machines that collectively provide multiple processors and a large main memory) can be used in order to speed up data processing. The advantages are twofold, since mass parallelisation: (a) could significantly reduce processing time as multiple cores can be used simultaneously, and (b) virtually alleviates the restriction on main memory as more memory can be easily added to the system.

However, there are certain issues that need to be addressed. More specifically, law would need to be encoded into some logic formalisation (e.g. defeasible logic) with potentially complex rules. In general, complex rules tend to hinder mass parallelisation as novel optimisations and efficient rule evaluation techniques would need to be developed. In addition, legal data itself (e.g. legal cases) would need to be studied in depth in order to comprehend the underlying patterns and data distribution. Data complexity might require special handling in order to ensure mass parallelisation. In addition, benchmarks that would resemble real-world legal data would need to be developed in order to prove scalability beyond current capacity.

5.2 Stream Reasoning

Stream reasoning has been studied in literature [19, 51], showing that only relatively simple rules could allow high throughput. In general, stream processing is intended for use cases where data is processed towards a single direction. However, in stream reasoning, recursive rules (i.e. rules that lead to inference loops) may lead to performance bottlenecks. In addition, within such a dynamic environment, incoming data could potentially invalidate previously asserted knowledge leading to a new set of knowledge, which would in turn change the set of conclusions.

Thus, legal reasoning on streaming data depends on the development of a wide range of novel methods that would be able to deliver high performance. This could lead to applications such as speeding up the process of case handling in courts since data can be processed while each case is examined; it could also be used by legal practitioners as a predictive system where different legal strategies are readily assessed.

5.3 Semantic Technologies

Existing work on semantic technologies can be used in proposed solutions for efficient legal reasoning to address, among others, the challenges in Section 4.3. The first question to be answered is related to the representation of data. Besides upper ontologies that provide definitions for a wide range of concepts, specialised legal ontologies such as LKIF [20] have been proposed. Thus, knowledge engineers have to decide whether the representation of data will be based on an existing ontology or to develop a new representation. In the second case, definitions of existing ontologies may be reused for providing semantic annotations of legal data.

Semantic Web tools and technologies such as large RDF stores and SPARQL querying engines can also be used for storage and querying of legal data. In addition, large scale reasoning solutions over RDF data can be used in a proposed solution; Triplewave [30] is an example of a large scale reasoning system over RDF stream data. Thus, a second question to be answered early on in the development of a legal reasoning solution is whether or not to use existing Semantic Web reasoning tools for all or some reasoning tasks.

5.4 Handling Inconsistencies

Research on data provenance of data has led to representation solutions such as the PROV ontology [33]. Although such provenance information is useful for identifying the quality of a data source, inconsistencies may still exist. Detecting inconsistencies and repairing them is a complex task. Proposed systems such as OntoRepair [32] are capable of detecting and repairing inconsistencies in ontologies but do not scale up to large datasets since both inconsistency detection (or ontology diagnosis) and automatic or semi-automatic repairing of ontologies is currently limited to non-parallel computing frameworks. Thus, research on parallelising diagnosis and repair over semantic data could prove useful. Alternatively, inconsistencies can be managed by exploiting approaches to reasoning that are inconsistency-tolerant, such as probabilistic or fuzzy reasoning and relational learning.

5.5 Simulation and Optimisation

Assessing the impact of legal change cannot be achieved by legal reasoning alone, since it requires techniques that are able to determine optimal configurations out of a set of available alternatives or to simulate the impact of what-if scenarios. An interesting direction would be to investigate hybrid solutions that combine legal reasoning with well-established methodologies in simulation and optimisation.

Considering the impact of traffic regulation on air pollution, simulation models can be built to determine the short and long-term impact of specific traffic parameters, such as speed or volume. Performing these simulation runs would result in a set of factors that are more impactful than others. Legal reasoning could then pinpoint the specific regulation clauses that pertain to these factors.

Alternatively, mathematical optimisation could also prove useful. For instance, to determine changes to traffic regulation that can keep air pollution within limits, legal reasoning can be performed on the existing regulation to determine traffic parameters, which can then be used to build a mathematical model representing their interaction and their effect on air pollution. The model would have an objective function that represents the distance of air pollution levels from the legal limit. Then, the goal would be to solve the optimisation problem of finding an optimal solution that minimises the objective function. This can be achieved either using optimisation algorithms or by relying on heuristics or meta-heuristics such as genetic algorithms.

6 Conclusion

This paper argued that there is scope for research in AI and law with regard to performing effective legal reasoning when the associated knowledge and data is on a large scale. We presented a number of potential scenarios where this kind of reasoning would be useful, with use cases ranging from the pharmaceutical, financial and property development sectors to food supply chains and impact analysis of regulatory change.

A series of technical challenges were identified and analysed in association with reasoning over big data. As should be expected these revolve around the so-called Vs of big data and involve: (a) handling large data volumes; (b) combining streaming data with existing legal knowledge; (c) integrating data from different sources and different formats; (d) determining provenance and improving quality of available data; and (e) effectively combining reasoning and analytic techniques.

Finally, we identified several directions for further research that are directly associated to the aforementioned challenges. In summary, we expect that legal reasoning over big data can benefit from research advances in relation to: (a) mass parallelisation of reasoning processes; (b) stream reasoning methodologies that can deliver high performance even within dynamic environments; (c) semantic technologies to represent, store and query large amounts of legal data; (d) data provenance, diagnosis and repair and reasoning approaches that can handle inconsistencies; and (e) hybrid solutions that combine simulation and mathematical optimisation with legal reasoning.

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