Integrating Natural Language and Formal Analysis for Legal Documents

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Abstract

Although much research has gone into natural language legal document analysis, practical solutions to support legal document drafting and reasoning are still limited in functionality. However given the textual basis of law there is much potential for NLP techniques to aid in the context of drafting legal documents, especially contracts. Furthermore, there is a body of work focusing on the formal semantics of norms and legal notions which has direct applications in analysis of such documents. In this paper we present our attempt to use several off-the-shelf NLP techniques to provide a more intelligent contract editing tool to lawyers. We exploit these techniques to extract information from contract clauses to allow intelligent browsing of the contract. We use this surface analysis to bridge the gap between the English text of a contract and its formal representation, which is then amenable to automated deduction, specifically it allows us to identify conflicts in the contract.

1. Introduction

Many fields of inquiry that have traditionally fallen under humanistic studies have benefited from the development of language technologies. For example, computational linguists have investigated several aspects of literary text and, more generally, "creativity", yielding important insights into the mechanisms underlying the creation of such texts (Gervás, 2013). One area of the humanities that has been the focus of increasing interest in recent years is legal studies.

The legal profession is wide and varied, however a good amount of legal work involves the drafting of documents, specifically contracts. Contracts are themselves linguistic artefacts and amenable to NLP techniques such as keyword and named entity extraction. Tools which leverage such NLP techniques to bridge between the linguistic "surface" structure of a contract and the underlying technical and logical content, have the potential to do for the drafting of contracts what intelligent design solutions have done for architects and engineers. Some tools already exist that provide some form of help to the contract drafter, e.g. (Gabbard et al., 2015); however what is lacking is an actual analysis of the semantics of the text, that is, a bridge between the language and the underlying semantics.

Contracts have drawn the attention of researchers interested in the formalisation of some of their features, such as norms, rights and obligations, often using some form of deontic logic (Fenech et al., 2009; Gao and Singh, 2014). Such formalisations constitute an abstraction of core aspects of the content of a contract, supporting reasoning and detection of errors and/or conflicts. However there remains a gap between the linguistic "surface" of a contract document, and its underlying structure and semantics. As a result, software tools that genuinely support contract editing, by providing on-demand analysis and reasoning of the linguistic content of a contract, remain scarce.

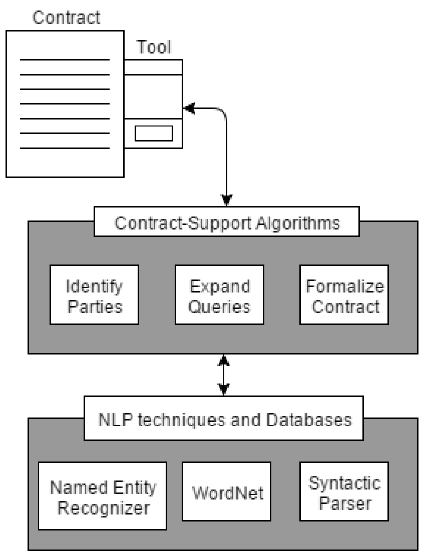


Figure 1: Three-layered (UI, Contract-Support, and NLP and Databases) tool architecture.

The present paper seeks to address this gap. In particular, we describe work on an intelligent contract editor which (a) exploits well-understood NLP techniques to extract information from the text as it is being drafted, using this (b) to enable intelligent browsing of contract clauses, and (c) to automatically construct a partial formal representation that supports automated reasoning about the core elements of the contract.

2. Architecture

In designing the tool we were motivated by the need to have an extensible architecture in order to support the integration of further external tools in order to allow the inclusion of new features in the tool and to improve the quality of the analysis we are already performing. As shown in Figure 1, the architecture is split into three modules that encapsulate the UI, the contract-support algorithms, and the off-the-shelf NLP tools and databases. In each module, a component-based approach is also taken, keeping each algorithm separate, and using dependency injection to enable exchange of these components without the need to change and re-compile the system.

Off-the-shelf NLP tools, such as dependency parsers and part-of-speech taggers (with multiple tools included in both cases), are also included in the system. To integrate them into our system (written in C#), the architecture exploits loosely coupled modules and C# wrappers for the off-the-shelf tools to enable interfacing with the tool.

3. Information Extraction

Our contract-editing tool is implemented as an add-in to Microsoft Word, allowing analysis of the contract side-by-side with contract editing. For this we exploit several information extraction algorithms, whose output we then associate with each contract clause as a set of features.

We developed an algorithm that uses a mixture of regular expressions and named entity extraction to identify the parties to the contract. Since the structure of contracts depends on the drafter, rather than on some universal template, this is not always effective; thus we allow the user to specify these themselves to further refine the outcomes.

We use keyword and named entity extraction in this manner, such that each clause is labelled with the keywords specific to it and the named entities mentioned by it, along with the parties mentioned.

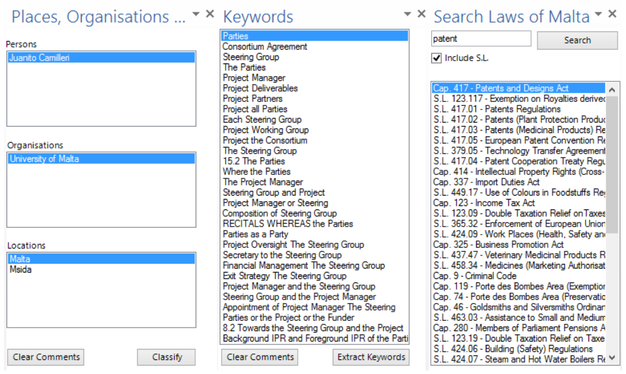
These sets are used to enable the user to browse the contract in question quickly, by highlighting the specific keyword, party, and/or entity in question. This can be useful, for example, to identify clauses which talk about a certain party or a specific concept (e.g. clauses involving a payment, or involving a specific party).

Drafting contracts can also require or benefit from cross-referencing against a body of legal text, including a country's laws or other relevant legal documents. Thus, our tool also includes the capacity to search through laws and related documents. (For the time being, this functionality uses a database consisting of the laws of Malta.) A database containing information about companies is also included, to allow cross-referencing with official company details which are important to get right in a contract.

To improve on both the results of these searches and the clause browsing we employ query expansion. Here, a user's search term is expanded using synonyms, as well as hypernyms and hyponyms which are within a fixed distance from the query in the Wordnet lexical database (Miller, 1995).

4. Formal Analysis

Extracting sufficient information from a contract to support such reasoning remains an understudied problem. Indeed, most approaches to legal texts that apply NLP techniques tend to view the task as a form of information retrieval whose results are insufficient to support automated reasoning (Gao and Singh, 2014; Dragoni et al., 2015; Wyner and Peters, 2011).



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Cap. 280 - Members of Parliament Pensions A
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S.L. 424.07 - Steam and Hot Water Boilers Re

Figure 2: Task pane views of law search, keyword and named entity extraction.

Reasoning about contracts can be done by modelling these using deontic logic (Von Wright, 1999), which views contracts as agreements between two or more parties, with norms (i.e. obligations, permissions, and prohibitions) and structures over these (e.g. temporal sequential composition). To bridge the gap between a natural language contract and such a model we have constructed a deontic logic that we can use to reason about a contract which is only partially known. This is important primarily in case of inaccuracies in the outcomes of the algorithm used to translate English contracts to their formal representation, but is also intended to help during contract-drafting, when the contract is not yet complete.

Definition 1 illustrates a simple subset of the deontic logic we use, without partiality, for simplicity of illustration. Note how the deontic norms are modelled as predicates over an action α, labelled with the acting party p. Simple contract clauses can then either be an obligation (O), a permission (P), or a prohibition (F). These clauses can then also either be sequentially composed ($C \rhd C'$), reparated[1] ($C \blacktriangleright C'$), concurrently composed ($C\&C'$), or conditioned on actions occurring ($[e]C$).

Definition 1. *A contract C, where α is an action label and p is a party label, is defined as follows:*

$$\begin{array}{rcl} C & := & O_p(\alpha) \mid P_p(\alpha) \mid F_p(\alpha) \mid [e]C \mid \\ & & C \rhd C \mid C \blacktriangleright C \mid C\&C \\ e & := & \alpha \mid 0 \mid 1 \mid e.e \mid e+e \mid e\&e \end{array}$$

Our approach to translate English contracts into this formal representation uses syntactic parsing. Consider, for example, the sentence "The passenger should check in" (an obligation clause). Structurally, this has the form **S** $\rightarrow$ **NP (VP** $\rightarrow$ **MD VP')**, as in Figure 3. Note how this structures the sentence such that it separates the party **(NP** $\rightarrow$ **the passenger)**, the norm **(MD** $\rightarrow$ **should)**, and the action **(VP'** $\rightarrow$

[1]A reparation clause C' for a contract C comes into effect if and after C is violated.

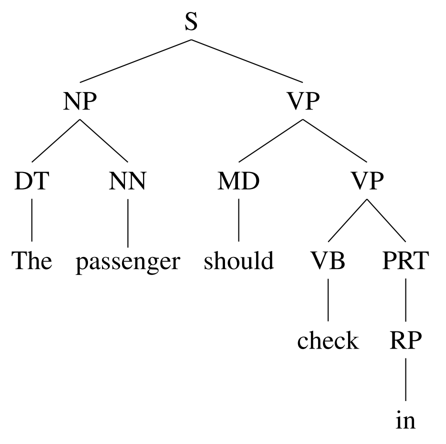

Figure 3: Parse tree of a normative sentence.

check in) into different sub-trees. Our approach is to 'read off' these aspects of the sentence's argument structure from the parse tree, mapping them to elements of our formalism.

To extract these from a sentence we define a number of pattern-matching expressions using Tregex (Levy and Andrew, 2006), which allows us to separately grab exactly the relevant features of a normative sentence. Thus with an appropriate expression we can get the formal counterpart of the clause, i.e. $O_{\mathit{passenger}}(\mathit{checkIn})$, indicating an obligation on the passenger to check in. We have defined several such expressions that correspond to a certain parse tree structure (along with the presence of a norm specifier like *should*, or *permitted to*). Although it is not clear whether such constructions always correspond to a normative sentence (e.g. "The receptionist should have been here" does not specify an obligation, although it can be seen to imply a perceived one), in the limited context of contracts this is quite likely, given that the phrasing of such constructs typically follows well-worn templates.

This approach is however limited by the number of expressions defined (and their quality). Another issue is that some sentences may not have correlates in our logic e.g. a distinction is made between state-based and action-based clauses, between which there is no one-to-one correlation (Hage, 2001).

With this formal representation we can detect conflicts automatically, through an appropriate trace semantics (e.g. $O_p(a)$ is satisfied if a is done, while $C \rhd C'$ is satisfied if C is satisfied, after which C' applies and is satisfied). We generate an automaton with states labelled with the applicable norms there, and transitions by actions, according to the trace semantics, and using the minimal method delineated in (Fenech et al., 2009). We axiomatise conflicts as in Definition 2, from (Pace and Schapachnik, 2012). By comparing the contracts at the states of the generated automaton we can detect any conflicts and report back to the user.

Definition 2. *Two contracts are said to be in conflict if there is no trace that satisfies both at the same time. The conflict relation is denoted by* $\maltese$*, so that that* C *and* C' *are conflicting is denoted by* $C \maltese C'$*. Note also that we denote two mutually exclusive actions as* $a \bowtie a'$*.*

Contract	TP	TN	FP	FN	Precision	Recall	F_1	$F_{0.5}$
C14	14	33	5	2	0.739	0.875		
C21	9	170	56	0	0.139	1		
C41	16	61	9	0	0.64	1		
C69	12	37	4	0	0.75	1		
C199	5	37	18	10	0.217	0.333		
Results					0.497	0.842	0.625	0.541

Table 1: Formalizing norms evaluation.

Axioms:

$$\vdash P_p(a) \maltese F_p(a) \tag{1}$$
$$\vdash O_p(a) \maltese F_p(a) \tag{2}$$
$$a \bowtie a' \vdash O_p(a) \maltese O_p(a') \tag{3}$$
$$a \bowtie a' \vdash O_p(a) \maltese P_p(a') \tag{4}$$
$$C \maltese C' \vdash C' \maltese C \tag{5}$$
$$C \maltese C' \wedge C' \equiv C'' \vdash C \maltese C'' \tag{6}$$

5. Evaluation

We evaluated our research in two ways: (i) by testing our English to deontic logic translation on a random selection of contracts from the Australian Contract Corpus (Curtotti and McCreath, 2011); and (ii) by obtaining feedback from notaries who used the Microsoft Word add-on over a few days.

As our gold-standard we selected five contracts from the corpus (of varying length), and hand-tagged each clause with a suitable representation in our logic, where possible. Clauses were also tagged as *normative* or not, and as *formalizable* in our logic or not.

The results of the automated translation are shown in Figure 1. In our evaluation, true positives correspond to those clauses which can be formalized and have been formalized correctly; while false positives correspond to the clauses which cannot be formalized but have still been (incorrectly) formalized. True negatives are clauses that cannot be formalized and were not attempted, while false negatives are clauses that can be formalized but were not.

As can be seen the amount of false positives is not negligible, especially with contracts **C21** and **C199**. Through an analysis of their text we observed that these false positives mostly occur in the definitions section of these contracts. These are only tagged as normative (since norm specifiers were present), but with the translation failing. Methods however exist to extract definitions automatically (e.g. (Curtotti et al., 2013)) which can be employed to preprocess the contract and dealing with definitions separately, thus improving the algorithm.

The tool as a whole was given to a number of notaries who were informally asked to give feedback after using it for a few days. Feedback received on the search functionality, especially in legal documents and companies, was mostly positive, or neutral among users who said they rarely consult such already available online databases. The other features were not perceived as useful, although it was pointed out that they may be more applicable in the context of large contracts.

6. Discussion

Our tool thus effectively combines existing NLP tools and formal contract analysis algorithms, providing for a degree of automated analysis. However, there are other features that we did not consider that would make the tool more attractive to notaries, such as a templating system, easing the analysis of definitions (e.g. (Curtotti et al., 2013)), a versioning system (a work-in-progress), or a higher-level analysis of the components of a contract (e.g. (Gabbard et al., 2015)).

On the formal side our approach also has some limitations. A major one is the fact that we check for equality between actions simply by checking for string equality. A better measure of equality can be added to our algorithm by semantic similarity measures that use a lexical database to analyse the senses of a word, as done in (Aires et al., 2015).

The logic used needs to be augmented with state-based norms as first-class entities, since these too appear in contracts, though seemingly at a lesser incidence then action-based ones. An example of such a norm is "The passenger should be in possession of their passport during the whole trip", which we detect automatically by noting the use of "be"[2].

7. Conclusions

Professionals involved in contract-drafting have the potential to benefit from tools that employ NLP techniques that can automatically analyse the contract while it is being written. This is an area of the humanities where NLP tools have yet to make a noticeable impact.

In this paper, we have presented a tool, packaged as an add-in to Microsoft Word, that presents several legal-drafting support features as task panes. These employ keyword and named entity extraction so as to facilitate the extraction of certain key words associated with each clause, to enable easier browsing of a contract depending on these keys.

We also employ a deontic logic, and syntactic parsing to automatically (partially) translate an English contract into a deontic logic model from which automated deductions can be made. Specifically conflicts between clauses can be detected.

The tool was tested by lawyers and notaries, getting overall positive feedback with suggestions for further work (e.g. including contract templates), with the law and company search being seen as the most useful, and automated deduction as promising.

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[2]There does not exist a single action a such that for this example we can construct a norm $O_p(a)$, i.e. a norm which is satisfied by the performance of a single action.