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Populating Legal Ontologies using Semantic Role Labeling

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Abstract

This paper is concerned with the goal of *maintaining* legal information and compliance systems: the 'resource consumption bottleneck' of creating semantic technologies manually. The use of automated information extraction techniques could significantly reduce this bottleneck. The research question of this paper is: How to address the resource bottleneck problem of creating specialist knowledge management systems? In particular, how to semi-automate the extraction of norms and their elements to populate legal ontologies? This paper shows that the acquisition paradox can be addressed by combining state-of-the-art general-purpose NLP modules with pre- and post-processing using rules based on domain knowledge. It describes a Semantic Role Labeling based information extraction system to extract norms from legislation and represent them as structured norms in legal ontologies. The output is intended to help make laws more accessible, understandable, and searchable in legal document management systems such as Eunomos (Boella et al., 2016).
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1. Introduction

This article is concerned with a major obstacle to the goal of maintaining legal information and compliance systems: the 'resource consumption bottleneck' (Hepp, 2007) of creating semantic technologies manually. Information extraction techniques could significantly reduce this bottleneck. However, it has been argued (Lenci et al., 2009) that:

> *Technologies in the area of knowledge management and information access are confronted with a typical acquisition paradox. As knowledge is mostly conveyed through text, content access requires understanding the linguistic structures representing content in text at a level of considerable detail. In turn, processing linguistic structures at the depth needed for content understanding presupposes that a considerable amount of domain knowledge is already in place.*

The research question of this article is: How to address the resource bottleneck problem of creating specialist knowledge management systems? In particular, how to semi-automate the extraction of definitions, norms and their elements to populate legal ontologies?

This article shows that the acquisition paradox can be addressed by combining state-of-the-art general-purpose NLP modules with pre- and post-processing using rules based on domain knowledge. The output is intended to help make laws more accessible, understandable and searchable in a legal document management system.

Research on ontology learning (creating new ontologies) and ontology population (populating existing ones) is an important field of ontology engineering, albeit not without limitations: "*none of the methods used today are good enough for creating semantic resources of any kind in a completely unsupervised fashion, albeit automatic methods can facilitate manual construction to a large extent*" (Biemann, 2005). While ontologies can be learned from structured and unstructured data, most research on ontology population concerns extracting data from unstructured text.

Many concepts and ontological relations can be extracted based on simple patterns such as "X, Ys and other Zs" and "Ws such as X, Y and Z" (Hearst, 1992) to extract IS-A relations or similar patterns to find PART-OF relations (Berland and Charniak, 1999).

For frame-based ontologies, we need to look at information extraction, in particular template filling. Traditionally, information extraction is approached in a supervised manner based on a set of examples expressing the relations or entities and constructed manually. Simple Information Extraction (SIE) (Giuliano et al., 2006) is a modular information extraction system designed to be easily and quickly portable across tasks and domains. SIE is composed of a general purpose machine learning algorithm, the Support Vector Machine (SVM), combined with several customisable modules. A crucial role in the architecture is played by an instance filtering module, which is based on the assumption that entities to be recognised are unlikely to have low information content (Gliozzo et al., 2005).

The core of many unsupervised information extraction systems (Yangarber et al., 2000)(Stevenson and Greenwood, 2005), are 'paraphrasing' modules to generate semantically equivalent components with lexical or syntactic variation. The synonym sets in the WordNet (Miller et al., 1990) general-purpose lightweight ontology are also very useful for this purpose (Moldovan and Rus, 2001)(Mihalcea and Moldovan, 2000). Syntactic word order patterns, such as active/passive formulations can be generated according to standard template rules and grouped together in equivalence classes. The TEASE system (Szpektor et al., 2004) is a generic paraphrasing extraction system that extracts relations between a pivot (lexical entry) and a template (dependency parse fragment). The surrounding words of the lexical entries are used as anchor sets to extract templates.

An alternative approach to handling language variability is to transform WordNet concept definitions into logical forms designed to be as close as possible to natural language (Rus, 2002). The notation module was developed for a question-answering system. The answer extraction procedure consisted of four steps: transforming questions and answers into logic forms, forming WordNet-based lexical chains between pairs of concepts, unifying lexical chains, and extracting inferences. However, this approach has already been tried and tested on legal text, using C&C/Boxer (Curran et al., 2007) to extract norms from UK citizenship legislation (Wyner, 2012). It was found that such systems perform better on Controlled English than NL constructions typically found in legislative text.

An alternative approach used in information extraction for the legal domain is semantic annotation of text, creation of a gold standard, and development of automated annotation tools (Wyner and Peters, 2012) (Wyner and Peters, 2011). The Teamware system uses the open source General Architecture for Text Engineering (GATE) tool for information extraction ((Cunningham et al., 2002)) to pre-annotate the text, thereby removing some aspects of the annotation task for domain experts.

There is much information extraction research involving machine learning in the legal domain (Adebayo et al., 2016). Of particular relevance to this article is the extraction of active roles, passive roles and involved objects in norms (Boella et al., 2012). Based on the idea that a semantic tag may be characterised by limited sets of syntactic contexts, their supervised Machine Learning approach involves the use of syntactic dependencies as factors in a Support Vector Machine classifier (Boella et al., 2013). Pattern-matching and machine learning has also been used to extract commitments, authorisations, powers, prohibitions and sanctions (Gao and Singh, 2014) or temporal relations (Robaldo et al., 2011).

They identify norms based on use of modal verbs. They use a classifier for identifying norms using verb and clause conjunctions. Elements of norms are extracted based on heuristics such as ‘If a norm sentence has a subordinate clause led by conjunction words such as “if” and “unless”, the subordinate clause expresses the antecedent. Other machine learning approaches for classifying norms and extracting elements of legislation (Grabmair et al., 2011) (Biagioli et al., 2005) rely entirely on the costly labour-intensive task of annotating legal corpora.

2. Semantic Role Labeling

Semantic Role Labeling (SRL) has emerged as a suitable intermediary for unsupervised information extraction (Surdeanu et al., 2003). SRL is the task of detecting basic event structures in a sentence such as “who” did “what” to “whom”, “when” and “where” (Màrquez, 2009). A semantic role (also known as thematic role, theta role or case role) is the underlying relationship that a participant has with the main verb in a clause (Loos et al., 2004).

Many verbs allow a variable number of semantic roles to be realized in various syntactic positions (diathesis alternations), as can be seen in the following abbreviated example from (Martin and Jurafsky, 2016):

```
[The rock/INSTRUMENT] broke
[the window/THEME].
[The window/THEME] was broken by
[John/AGENT].
```

While an agent or instrument can both be the grammatical subjects of a sentence, a sentence such as “John and a hammer broke the window.” is grammatically unacceptable. (Fillmore, 1968) explained why: only noun phrases representing the same *case* may be conjoined. In ancient Greek or Russian, the phrase ‘with a rock’ in the sentence “John broke the window with a rock” would be expressed with a single noun with the instrumental case marker, which is different from the nominative case used for “John”. In English, the instrumental case is ‘flagged’ by the preposition ‘with’. However, there is no rigid one-to-one mapping between flags and cases -‘with’ can also flag the cases ‘Manner’ (‘with glee’) and ‘Accompanier’ (‘with Nadia’) ((Hirst, 1992)). (Levin, 1993) noted that syntactic constraints on verbs and the arguments they may take are semantically determined, and created verb classes whose members pattern together with respect to diathesis alternations.

There is no consensus on a definitive list of semantic roles ((Màrquez et al., 2008)) that should be used for semantic role labeling. In FrameNet ((Fillmore et al., 2004)), which is based on frame semantics ((Fillmore, 1976)), arguments are related to deep roles related to specific scenarios or frames, such as Suspect, Authorities and Offense. PropBank ((Kingsbury and Palmer, 2002)), on the other hand, uses general roles and verb-specific roles based on the verb classes of (Levin, 1993). The roles are numbered, rather than given semantic names, although in general, Arg-0 corresponds to Agent while Arg-1 corresponds to Patient. Both FrameNet and PropBank use extra-thematic elements such as Time, Manner and Place. (Màrquez et al., 2008) assert that most research on SRL is now conducted on PropBank, mainly because of its greater coverage.

SRL systems rely on automated part-of-speech tagging and parsing. Most SRL systems use constituency parsers, probably because they have traditionally been better resourced for the English language. However, (Johansson and Nugues, 2008) argue that dependency structures offer a more transparent encoding of predicate argument relations (e.g. grammatical function such as subject and object is an integral concept in dependency syntax) and thus dependency structures are more suitable for explaining the syntax-semantics interface ((Mel?čuk, 1988)). Moreover, in their comparison of constituent-based and dependency-based SRL systems for FrameNet, they found that their performance was roughly the same, except that dependency-based systems outperformed constituent-based systems when using out-of-domain test sets, due to their lesser reliance on lexical features ((Johansson and Nugues, 2008)). Another reason for choosing SRL systems based on dependency parsers is that they can be more efficient ((Ciaramita et al., 2008)), rendering them more suitable for real-life applications ((Surdeanu et al., 2008)).

Most automated SRL systems follow this three step architecture: i) filtering (or pruning) the set of argument candidates for a given predicate; ii) local scoring of argument candidates for possible role labels, including a ‘no-argument’ label; and iii) joint scoring to combine the predictions of local scorers and ensure that the eventual labeling satisfies structural and SRL-dependent constraints. The Mate Tools Semantic Role Labeler ((Björkelund et al., 2009)) used for this article follows this architecture.

3. Extracting Structured Norms

FrameNet based methodologies for extracting norms have been presented in (Venturi et al., 2009) and (Bertoldi and de Oliveira Chishman, 2011), among others. On the other hand, PropBank Semantic Role Labeling has been used in legal informatics for Abstract Meaning Representation (AMR)(Viet et al., 2017) and event extraction for legal case retrieval(Maxwell et al., 2009). Other proposals propose whole legal ontologies for representing concepts in norms (Ajani et al., 2017), (Palmirani et al., 2018a), (Palmirani et al., 2018b). This paper describes the extraction of structured norms from legislation using a PropBank Semantic Role Labeler ((Kingsbury and Palmer, 2002)). It is submitted that this approach could achieve wider coverage than FrameNet ((Fillmore et al., 2004)), as has been the observation in other information extraction research (e.g. (Kaisser and Webber, 2007)). Moreover, the use of shallow rather than deep roles allows for greater flexibility in the selection and classification of data extracted, tailored to the requirements of the relevant application.

To extract norms, sets of rules were devised which in cascade identify possible norms, classify their types, and then on the basis of their types, use further rules to map arguments in a Mate Tools Semantic Role Labeler (SRL) semantic role tree to domain-specific slots in a legal ontology. The input to the SRL is normalised text of legislation, making legislative text akin to standard written text to facilitate information extraction. The normalisation module incorporates pattern-matching and the (Brill, 1992) part-of-speech tagger in the Python Natural Language Toolkit (NLTK) by (Bird, 2006) to tokenise, transform lists into regular sentences, and transform references and citations to avoid parsing errors. The normalised text is then transformed into an input file with a word index and word surface on each line. The output is a table of semantic role dependencies, in accordance with the specification of The CoNLL-2009 Shared Task ((Hajič et al., 2009)).

The methodology for extracting norms relies on sets of rules to identify: sentences containing norms, the norm type, and the roles in the SRL tree to map to slots in a legal ontology, with further rules as necessary for extracting nested norms, conditions, exceptions, etc. Below we illustrate this methodology applied to different norm types.

3.1. Definitions

Populating a legal ontology based on a bottom-up approach necessarily involves the laborious task of storing definitions from all relevant legislation. While most definitions are in the Definitions section of relevant legislation and follow the regular 'definiendum equals definiens' form, there are other less obvious definitions, often found in the normative provisions, which are highly influential.

One such type is definition by example. The examples are typical, and invite extension by analogy, so there is a sense of completeness. Include/example definitions, on the other hand, are incomplete, and are often used to emphasise the inclusion or exclusion of items where this would otherwise be uncertain or even surprising.

For space reasons, we illustrate here only the regular definition type. Here is one example from Directive 98/5/EC[1]

```
For the purposes of this Directive: 'host
Member State' means the Member State in which
a lawyer practises pursuant to this Directive;
```

The definiendum and definiens are extracted in accordance with SRL roles. For regular definitions, the Definition is the A1 (SBJ) of the relevant predicate (usually a verb), the Definiens is the A1 (OBJ) and Reason is AM-ADV (ADV). In addition to the traditional 'Definition' and 'Definiens' elements found in all ontologies, we also have the element 'Scope'. Our XML output is:

```
<Norm>
  <NormType>Definition</NormType>
  <Definiendum>host Member State</Definiendum>
  <Definiens>the Member State in which
    a lawyer practises pursuant to
    this Directive</Definiens>
  <Scope>for the purposes of this
    Directive</Scope>
</Norm>
```

Based on analysis of the training corpus, the following patterns of parser dependencies were collated for the predicates used for regular definitions (where → indicates sequence and bracketed items are parts of speech):

- Head → means (VBZ)
- Head → any sequence of words → means (VBZ)
- Head → shall (MD) → mean
- Head → constitutes (any POS)
- Head → any sequence of words → defined (any POS)

3.2. Obligation

Consider for example the passive sentence below from 2007/60/EC[2], which represents an obligation:

```
Hence, objectives regarding the management
of flood risks should be determined by the
Member States themselves and should be based
on local and regional circumstances.
```

Figure 1 shows that the SRL tool understands that the agents (role A0) are the Member States, relegating the objectives to the object (A1) role of the verb 'determine'. Moreover, it also abstracts from the fact that the root of the parse tree is the modal verb followed by an auxiliary. Thus it becomes simpler to write rules on the SRL output than on the parse tree. The XML output is:

```
<Norm>
  <NormType>Obligation</NormType>
  <ActiveRole>Member States themselves
```

[1]Directive 98/5/EC of the European Parliament and of the Council of 16 February 1998.

[2]Directive 2007/60/EC of the European Parliament and of the Council of 23 October 2007 on the assessment and management of flood risks (Text with EEA relevance).

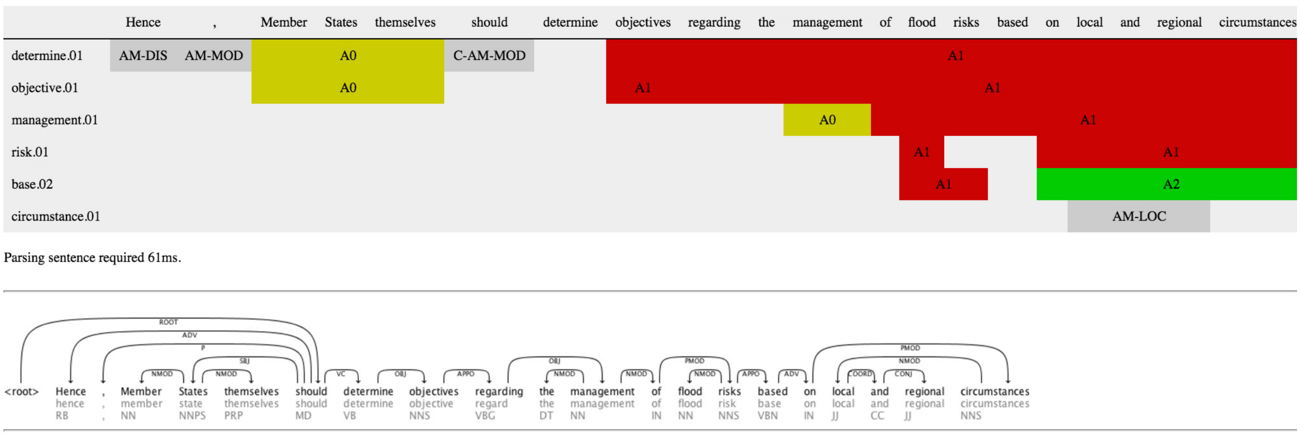

Figure 1: SRL extraction of an active obligation

```
    </ActiveRole>
  <Action>objectives regarding the
  management of flood risk should be
  determined and should be based on local
  and regional circumstances</Action>
</Norm>
```

If we convert this sentence to an active sentence, the elements extracted are practically the same (figure 2).

3.3. Right

Here is an example from Directive 98/5/EC[1]:

```
Any lawyer shall become entitled to pursue
on a permanent basis, in any other Member
State under his home-country professional
title, the activities specified in Art.5.
```

The path to root is [[u'shall', u'MD', 2], [u'become', u'VB', 3], [u'entitled', u'VBN', 4]]. Converting the SRL roles A2:SBJ to ActiveRole and A1:OPRD to Action we obtain the following structured norm:

```
<Norm>
  <NormType>Right</NormType>
  <ActiveRole>Any lawyer</ActiveRole>
  <Action>to pursue on a permanent basis,
    in any other Member State under his
    home-country professional title, the
    activities specified in Art.5</Action>
</Norm>
```

3.4. Permission

Here is an example from Directive 98/5/EC[1]:

```
A lawyer registered in a host Member State
under his home-country professional title may
practise as a salaried lawyer in the employ
of another lawyer, an association or firm of
lawyers, or a public or private enterprise to
the extent that the host Member State so
permits for lawyers registered under the
professional title used in that State.
```

The modal verb 'may' as head of the sentence indicates that the type of norm is a Permission. The verb 'practice' is dependent on the head, and used as the 'predicate' from which to extract arguments for the ontology. Converting the SRL roles A0:SBJ to ActiveRole and A2:ADV to Action, the keywords 'to the extent' in the A2 argument triggers a rule to extract the Condition as a separate field to the Action. The final structured norm is as follows:

```
<Norm>
  <NormType>Permission</NormType>
  <ActiveRole>A lawyer registered in a host
     Member State under his home-country
     professional title</ActiveRole>
  <Action>practise as a salaried lawyer in
     the employ of another lawyer, an
     association or firm of lawyers, or a
     public or private enterprise</Action>
  <Condition>to the extent that the host
     Member State so permits for lawyers
     registered under the professional title
     used in that State</Condition>
</Norm>
```

3.5. Power

Power is the ability to change legal relations. In EU legislation, we find the exercise of powers to delegate the creation of obligations to national parliaments and beyond.
Here is an example from Directive 98/5/EC[1]:

```
It may require that, when presented by
the competent authority of the some
Member State, the certificate be not
more than three months old.
```

The path to the tree, [['may', 'MD', 1], ['require', 'VB', 2]], is an instance of a rule that identifies a path [['may', MD],['require', ANYPOS] as a candidate for argument extraction, and identifies this as a pattern of a Power. Note that the default norm type for a norm with the modal verb 'may' is Permission, but 'power' verbs such as 'require' trigger an exception to this rule.
The action element could be further analysed by additional sets of rules, taking advantage of the analysis of the SRL, to understand a condition (AM-TMP):

```
<SRL>
    <PREDICATE>be</PREDICATE>
```

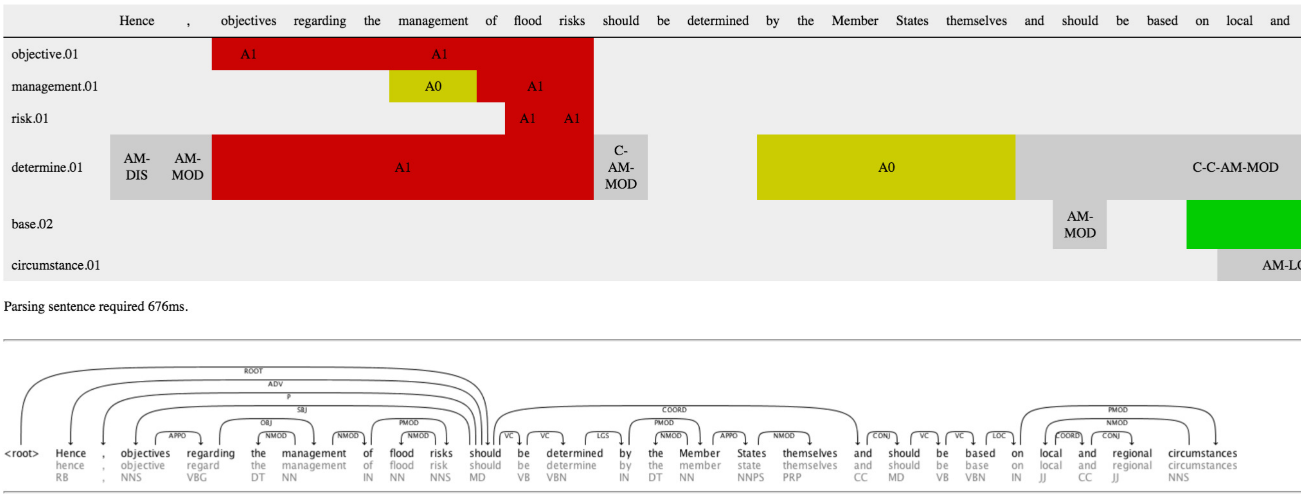

Figure 2: SRL extraction of a passive obligation

```
    <AM-TMP>when presented by the competent
       authority of the home Member State
       </AM-TMP>
    <A2>not more than three months old</A2>
</SRL>
```

The sentence can be viewed as containing two separate norms, a Power and a (conditional) Obligation. Or it may be seen as a nested Power norm, as represented below.

```
<Norm>
  <NormType>Power</NormType>
  <ActiveRole>It</ActiveRole>
  <Norm>
    <NormType>Obligation</NormType>
    <Action>the certificate be not more than
       three months old</Action>
    <Condition>when presented by the
       competent authority of the home
       Member State</Condition>
  </Norm>
</Norm>
```

3.6. Legal Effect

There are certain legal statements that state that when a condition is satisfied, a certain legal effect takes place without any particular action on the part of any addressee. Here is an example from Directive 98/5/EC[1]:

```
Although it is not a prerequisite for the
decision of the competent authority in the
host Member State, the temporary or
permanent withdrawal by the competent
authority in the home Member State of the
authorisation to practise the profession
shall automatically lead to the lawyer
concerned being temporarily or permanently
prohibited from practising under his home-
country professional title in the host
Member State.
```

The roles of the predicate ‘lead’ in the SRL output (shown below in XML) can be conveniently mapped after normalisation to slots in an ontology: A0:SBJ to Situation, A2:ADV to Result, and AM-ADV:ADV to Condition.

```
<Norm>
  <NormType>Legal Effect</NormType>
  <Situation>the temporary or permanent
     withdrawal by the competent authority
     in the home Member State of the
     authorisation to practise the
     profession</Situation>
  <Result>the lawyer concerned is
     temporarily or permanently prohibited
     from practising under his home-country
     professional title in the host Member
     State</Result>
  <Condition>it is not a prerequisite for
     the decision of the competent
     authority in the host Member State</Condition>
</Norm>
```

The condition above is in truth a statement that a possible condition does not apply. The handling of alternative condition-like clauses remains a subject for future work.

3.7. Scope

Statements about scope are about the subject or object of a rule. Here is an example from Directive 98/5/EC[1]:

```
Irrespective of the rules of professional
conduct to which he is subjected in his home
Member State, a lawyer practising under his
home-country professional title shall be
subjected to the same rules of professional
conduct as lawyers practising under the
relevant professional title of the host
Member State in respect of all the
activities he pursues in its territory.
```

The pathToRoot is [[u‘shall’, u‘MD’, 26], [u‘become’, u‘VB’, 27], [u‘subjected’, u‘VBN’, 28]]. Mapping A1:SBJ to ActiveRole, A2:ADV to Rule and AM-ADV:ADV to Condition, the structured norm is:

```
<Norm>
  <NormType>Scope</NormType>
  <ActiveRole>a lawyer practising under his
  home-country professional title
```

```
  </ActiveRole>
  <Rule>to the same rules of professional
     conduct as lawyers practising under
     the relevant professional title of the
     host Member State in respect of all
     the activities he pursues in its
     territory</Rule>
  <Condition>Irrespective of the rules of
    professional conduct to which he is
    subjected in his home Member State
  </Condition>
</Norm>
```

Note again the non-condition in the Condition field.

3.8. Exception

Exceptions to norms can take place within the same sentence as a norm or outside (in which case, it usually pertains to the sentence norm before). Exceptions can be represented in different ways: as a separate entity with an 'Exception' relation to a norm, or as as an 'Exception' field within the norm itself. In the XML output of this research, it is represented as a separate entity. Here is an example of an Exception sentence from Directive 98/5/EC[1]:

```
Nevertheless, a lawyer practising under his
home-country professional title shall become
exempted from that requirement if he can
prove that he is covered by insurance taken
out or a guarantee provided in accordance
with the rules of his home Member State,
insofar as such insurance or guarantee is
equivalent in terms of the conditions and
extent of cover.
```

Mapping A1:SBJ to WhatIsExcepted, A2:ADV to ExceptedFrom and AM-ADV:ADV to Condition, we obtain the following structured norm:

```
<Norm>
 <NormType>Exception</NormType>
 <WhatIsExcepted>a lawyer practising under
   his home-country professional title
 </WhatIsExcepted>
 <ExceptedFrom>from that requirement
   </ExceptedFrom>
 <Condition>if he can prove that he is
   covered by insurance taken out or a
   guarantee provided in accordance with
   the rules of his home Member State,
   insofar as such insurance or guarantee
   is equivalent in terms of the conditions
   and extent of cover</Condition>
</Norm>
```

3.9. Hierarchy of Norms

The corpus contains statements expressing the hierarchy of one norm with respect to another. We need to have relations between norms that express relative hierarchy. As an intermediate step, we can extract a Hierarchy MetaNormType. This is an example from Directive 98/5/EC[1]:

```
Integration into the profession of lawyer in
the host Member State shall be subject to
Article 10.
```

The word 'subject' has been transformed by the normalising module into 'subjected' to allow the SRL module to extract arguments from the predicate.
Converting A1:SBJ to LowerPriority and A2:ADV to HigherPriority, we obtain the following structured norm:

```
<Norm>
  <NormType>Hierarchy</NormType>
  <LowerPriority>Integration into the
     profession of lawyer in the host
     Member State</LowerPriority>
  <HigherPriority>Article 10
     </HigherPriority>
</Norm>
```

3.10. Rationale

Directives provide the rationale for the existence of the legislation by stating its general purpose and referring to supporting preceding legislation. Here is an example from Directive 98/5/EC[1]:

```
The purpose of this Directive is to
facilitate practice of the profession
of lawyer on a permanent basis in a
self-employed or salaried capacity in a
Member State other than that in which the
professional qualification is obtained.
```

Having transformed each 'is' and 'are' to 'become' and 'becomes' to improve SRL performance, the pathToRoot here is [[u'becomes', u'VBZ', 5]]. The SRL output is then:
To populate an ontology, the contents of A2:PRD are placed in the <Purpose> field and the field Rule is populated with 'this Directive' within the context of a Rationale norm-type.

```
<Norm>
  <NormType>Rationale</NormType>
  <Rule>this Directive</Rule>
  <Purpose>to facilitate practice of the
     profession of lawyer on a permanent
     basis in a self-employed or salaried
     capacity in a Member State other than
     that in which the professional
     qualification is obtained</Purpose>
</Norm>
```

4. Evaluation

Before evaluating the performance of the system for extracting definitions and norms, it is worth taking into account the performance of the Semantic Role Labeler on legislative text. The system was tested on 224 sentences from Directive 95/46/EC[3], 58 definitions and 166 norms. For each sentence, the arguments for all the verb predicates in the sentences were evaluated, and the overall sentence was evaluated as accurate if all the arguments for all the verbs were correct. 78.5% of definitions had correct arguments for all verbs. However, only 52% of norms had the same. Generally, norms are more complex, and therefore more errors are introduced. Nevertheless, not all errors have consequences for the definition and norm extraction system, since only certain predicates are used by the system.

[3]Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995.

For space reasons, we omit from this section experiments conducted on legislation that formed part of the training data, and which showed a high degree of linguistic consistency across one piece of legislation.

The system was then tested on unseen legislation, Directive 95/46/EC[3] excluding the preamble and annexes. Table 2[4] shows the quantified results for each norm element. The strict (S) results take partially correct results as wrong whereas the lenient (L) results take them as being correct

The field NormType is relevant to all norms. Possible output were: Definition, Obligation, Permission, Power, Scope, Right, Hierarchy, Exception, Legal Effect and Unknown. All the norms classified as Unknown were in fact, actual norms of the relevant type, apart from one Proclamation which were not sought in the program. The evaluation also revealed a number of norms that should be classed as Liability, which are potential obligations arising from the Power of another to impose an Obligation. This reflects a level of uncertainty about whether such an Obligation will arise. On the other hand, it could be argued that Obligations arising from the Obligation of another to impose an Obligation have a greater level of certainty and should be (and have) been classed as Obligations. Most of the errors in determining the norm type (36%) arose from mistaking Powers for Permissions.The problem is that both types of norms have the modal verb 'may'. The module sought to deal with this by identifying 'Power' verbs that follow the modal, based on the corpus used to develop the system. However, the evidence of this evaluation shows that this is less than satisfactory. For EU legislation, it can be assumed that almost all norms involving the modal 'may' and having a Member State as an Active Role are Powers.

The other elements in Table 1 and table 2 are Definiendum, Definiens, Includes and Excludes, all elements that pertain to Definitions. The elements Action, Active Role, Passive Role, Condition, Timeframe, Exception and Reason pertain to norms of the type Obligation, Permission, Power and Right. The elements Situation and Result pertain to meta-norms of the type Legal Effect. The elements Object, Excludes Object and Active Role pertain to meta-norms of the type Scope. The elements Higher Priority and LowerPriority pertain to meta-norms of the type Hierarchy. There were few meta-norms in the legislation evaluated.

The results are very varied, and shows that further work is required to achieve acceptable results. However, the most important elements - Norm Type, Active Role - are obtained with good accuracy, which in itself should help most important search i.e. which obligations need to complied with.

One significant weakness, however, is the poor performance of the system on identifying Passive Roles. Moreover, apart from their identification, there are two aspects that require further consideration. Firstly, how to distinguish between beneficiaries of norms and other passive roles, such as agents who play an active role in a condition or exception. Secondly, how to relate the passive roles to the relevant parts of the norm.

The high Partially Correct results for the Action element reveals that it suffers the most from boundary errors. Boundary errors are also a problem for Conditions, Timeframes, Exceptions and Reasons. This is one particular area where the output of the SRL system is particularly disappointing. However, even when supplemented by pattern-matching, problems remain. 30 Fully Correct Conditions were identified via the SRL output as opposed to 21 via pattern-matching (keywords such as 'where' or 'when'). 41 Partially Correct were identified via SRL, 34 via pattern-matching. 35 elements were wrongly classified as Conditions via SRL, 27 via pattern-matching. 38 Conditions were missed altogether and 13 Conditions were wrongly classified as something else. The situation is similar for Timeframes and Exceptions, although there are fewer of those in the legislation evaluated. Some improvement could be made by deeper analysis of dependency trees. However, many of these problems arose due to problems with linking different elements of lists in the normalisation module, and this needs to be looked at further.

The low incidence of Scope and Hierarchy in this particular legislation makes it difficult to provide a proper evaluation of relevant elements.

5. Conclusions and Future Work

To address the resource bottleneck problem of creating specialist knowledge management systems, in particular how to semi-automate the extraction of definitions, norms and their elements to populate legal ontologies, we have described a definition and norm extraction system using semantic representations from a general-purpose SRL module (Björkelund et al., 2009). This solution was pursued in order to simplify the sets of rules required to identify possible norms and definitions, classify their types, and map arguments to domain-specific slots in a legal ontology.

There are a number of observations that have emerged from this evidence-based research. While much theoretical work on norms have focused on obligations, and there are indeed plenty of them in the legislation studied, there are also certain kinds of norms that are less prominent in the literature but are, nevertheless, important to cover in a comprehensive norm extraction system.

One element that requires further investigation is Passive Role, since this research found that there are many different kinds of passive roles, not only beneficiaries, and it would be useful to distinguish between them. Another element that requires further consideration is the Condition element. There are a number of constructions in legislative text regarding the applicability of norms that are somewhat similar to conditions, but have different effects. For instance, 'in particular' indicates that a norm applies in a particular scenario, but is not limited to that scenario. 'Notwithstanding' implies that what might be considered as a negative condition does not in fact apply. In addition to the Condition element, it is submitted that a Timeframe element could also be of value.

Other future work following from this research are: i) anaphora resolution specifically for legislative text, including references to entities in other articles; ii) Is-A and Part-Of relationships among defined entities; iii) generation of different views of a norm based on Hohfeldian correlatives;

[4]F-measure is calculated using precision and recall decimal values to 17 decimal points

Table 1: Accuracy of SRL extraction of elements of definitions and norms

Element	Correct	Partially Correct	Wrong (False Positive)	Missing (False Negative)	Misclassified as Different Element (False Negative)
Norm Type	184	N/A	66	17	N/A
Definiendum	6	8	0	2	0
Definiens	5	3	0	1	0
Includes	5	1	0	0	0
Excludes	0	0	0	3	10
Action	46	113	56	40	2
Active Role	113	6	10	33	10
Passive Role	13	15	5	90	4
Condition	30	41	35	38	13
Timeframe	11	11	9	6	0
Exception	4	13	1	7	7
Reason	2	2	6	9	0
Situation	0	0	5	1	0
Result	0	0	3	1	0
Object	1	0	0	0	0
ExcludesObject	0	3	2	3	0
HigherPriority	0	0	3	0	3
LowerPriority	0	0	0	0	0

Table 2: Precision, recall and F-measure of extraction of elements of norms (S = Strict, L = Lenient)

Element	Precision (S)%	Recall (S)%	F-Measure (S)%	Precision (L)%	Recall (L)%	F-Measure (L)%
Norm Type	73.60	91.54	81.60	73.60	91.54	81.60
Definiendum	42.86	75.00	54.55	100	87.5	93.33
Definiens	62.50	83.33	71.43	100	88.89	94.12
Includes	83.33	100	90.91	100	100	100
Excludes	0	0	0	0	0	0
Action	21.40	52.27	30.36	73.95	79.10	76.44
Active Role	87.60	72.44	79.30	92.25	73.46	81.79
Passive Role	39.39	12.15	18.57	84.85	22.95	36.13
Condition	28.30	37.04	32.09	66.98	58.20	62.28
Timeframe	35.48	64.71	45.82	70.97	78.57	74.58
Exception	22.22	22.22	22.22	94.44	54.84	69.39
Reason	20.00	18.18	19.05	40.00	30.77	34.78
Situation	0	0	0	0	0	0
Result	0	0	0	0	0	0
Object	100	100	100	100	100	100
Excludes-Object	0	0	0	60.00	50.00	54.55
Higher-Priority	0	0	0	0	0	0
Lower-Priority	0	0	0	0	0	0

iv) rigorous analysis of the relationship between norms to determine norms that may be satisfied in alternative ways, or must be satisfied as a group; v) advanced semantic representations based on avoidance of nestings, as advocated in (Robaldo, 2010a), (Robaldo, 2010b), and (Robaldo, 2011), or reification, as advocated in (Hobbs and Gordon, 2017).

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