Concept Recognition in European and National Law

Rohan NANDA [a,b,1], and Giovanni SIRAGUSA [a] and Luigi DI CARO [a] and Martin THEOBALD [b] and Guido BOELLA [a] and Livio ROBALDO [b] and Francesco COSTAMAGNA [a]

[a] *University of Turin, Italy*

[b] *University of Luxembourg, Luxembourg*

Abstract. This paper presents a Concept Recognition system for European and national legislation. Current named entity recognition (NER) systems do not focus on identifying concepts which are essential for interpretation and harmonization of European and national law. We utilized the IATE (Inter-Active Terminology for Europe) vocabulary, a state-of-the-art named entity recognition system and Wikipedia to generate an annotated corpus for concept recognition. We applied conditional random fields (CRF) to identify concepts on a corpus of European directives and Statutory Instruments (SIs) of the United Kingdom. The CRF-based concept recognition system achieved an F1 score of 0.71 over the combined corpus of directives and SIs. Our results indicate the usability of a CRF-based learning system over dictionary tagging and state-of-the-art methods.

Keywords. Concept Recognition, European Law, Information Retrieval

1. Introduction

With the increasing volume of European and national legislation available online, the identification of domain concepts in legal texts is very important for the development of legal information retrieval systems. The identification of domain concepts provides a deeper insight into the interpretation and understanding of texts. The recognition of concepts in legal texts would also be useful for the harmonization and integration of European and national law. Research in this domain has mainly focused on identification of named entities like person, organization and location names. However, European and national legislation contains very few instances of named entities. They primarily comprise legal and domain-specific jargon which can be represented by concepts.

In this paper, we develop a system for concept recognition in European directives and national law (statutory instruments of the United Kingdom). We chose directives as they are not directly applicable and need to be transposed into national law. Therefore, they may have more similar concepts with the national legislation than regulations or

[1] Corresponding Author

decisions. We chose statutory instruments (SIs) from the United Kingdom (UK) national law for our experiments. Most European Union (EU) directives are transposed by statutory instruments in the UK legislation [10]. The national measures which transpose the directive are called as national implementing measures (NIMs). Therefore, most of the SIs comprise NIMs and may have similar domain concepts with directives.

The concept recognition system was used for automatically identifying concepts in a corpus of 2884 directives and 2884 SIs. We generated an annotated corpus using a semi-supervised approach to save human effort and time for evaluation of our system. Further, we also generated a mapping to link similar terms in directives and SIs under the same concept.

The rest of the paper is organized as follows. In the next section, we discuss the related work. Section 3 describes the concept recognition system. Section 4 discusses the results and analysis. The paper concludes in Section 5.

2. Related Work

Related work is mainly focused in the domain of named entity recognition (NER) systems. NER systems identify text spans of entity mentions. These mentions are generally assigned to Person, Organization and Location names. In named entity linking, the mentions are linked to entities in a knowledge base on the basis of contextual similarity. In [1], the authors developed a legal named entity recognizer and linker by aligning YAGO[2] (WordNet-and Wikipedia-based ontology) and the LKIF [7] ontology. The alignment was carried out manually by mapping a concept node in LKIF to its equivalent in YAGO. They utilized different models like support vector machines (SVM), Stanford Named Entity Recognizer (NER) [5], and neural networks and evaluated the system on a small sample of judgements from the European Court of Human Rights (ECHR). Their results indicate that LKIF level of generalization is not suitable for named entity recognition and classification as their system was unable to distinguish between the classes defined in LKIF. However, their NER system achieved a better performance while distinguishing YAGO classes. The authors in [4] developed a named entity recognition and classification system to recognize entities like judges, attorneys, companies, courts and jurisdictions in US case law, depositions, pleadings and other trial documents. They utilized dictionary lookup, contextual pattern rules and statistical models for identifying named entities. The NER system was trained using a SVM classifier and evaluated on manually and automatically acquired training datasets of case law. The authors in [2], developed a NER system using AdaBoost. The system uses a window, along with a set of features (part-of-speech tags and dictionary of words) to capture the local context of a word.

Current NER systems are based on conditional random fields (CRF) [8], which allow to train a unique model for the classification and recognition of named entities. In [5], the authors developed a CRF which used Gibbs sampling instead of the standard Viterbi algorithm. They demonstrated that the use of Gibbs sampling allowed the system to distinguish between mentions of organization or person on the basis of context, thus enforcing label consistency. Ronan et al. [3] proposed a unified neural network model along with a CRF for NER and other natural language processing (NLP) tasks like part-

[2]http://www.yago-knowledge.org/

of-speech tagging, chunking and semantic role labeling. A neural network (typically a long short-term memory) [6] generates a matrix of size num_words $\times$ num_tags, which contains the score for each tag. This matrix is passed as input for the CRF. The main advantage of these models is their capability to capture important features from the word embedding, thus improving the performance of the CRF model.

3. Concept Recognition System

In this section, we describe the concept recognition system for European and national law. In the legal domain, concepts are generally represented using ontologies or vocabularies. Previous NER systems (based on the concepts represented in LKIF ontology) demonstrated that LKIF level of generalization was not suitable [1]. This is because NER systems could not clearly distinguish between the classes defined in LKIF. Therefore, in this paper we investigate the use of vocabularies for developing our concept recognition system . We utilize Inter-Active Terminology for Europe [3] (IATE), which is EU's inter-institutional terminology database. IATE is highly suitable for developing concept recognition systems because it is based on a concept-oriented[4] approach where each term is mapped to a concept. It provides both mono-and multilingual mapping between terms and concepts and thus can also be used to develop multilingual concept recognition systems for future work. IATE has 21 subject domains with one sub-level. The EuroVoc[5] thesaurus also offers the same 21 subject domains but with upto 6 sub-levels. Our initial hypothesis was to determine if we are able to recognize concepts and classify them to these 21 domains. For future work, we intend to utilize also the sub-domains to achieve a fine-grained hierarchical concept recognition. IATE consists of 1.3 million entries in English. Every entry (concept) in IATE is mapped to a subject domain. We filtered out some irrelevant entries in IATE (stopwords and concepts mapped to NO DOMAIN).

3.1. Annotated Corpus Generation

We utilized a corpus of 2884 directives and 2884 statutory instruments for our experiments. Since training data was not available, we utilized a semi-supervised approach to generate an annotated corpus. The development of NER or concept recognition systems require a large amount of manually annotated datasets, which is expensive to obtain [9]. We manually annotated few documents with IATE subject domains. Then we developed a dictionary lookup program to tag terms (both words and phrases) in the text with IATE subject domains. Each term in the text was compared to entries in IATE vocabulary and matching terms were tagged with the relevant subject domains. IATE consists of a mapping composed of the set of <multi-word expression, domain> pairs. We consistently improved the dictionary lookup program to match different multi-word expressions present in the IATE vocabulary. The IATE dictionary as a function ϕ for a document d produces a set of candidate subject domains $\phi(d) = \{d_1, d_2, \ldots, d_n\}$. We also used spaCy[6], a state-of-the-art NER system to annotate some entities like time, date

[3] http://iate.europa.eu
[4] http://iate.europa.eu/tbx/IATE%20Data%20Fields%20Explaind.htm
[5] eurovoc.europa.eu/
[6] https://spacy.io/

and money. After this tagging by IATE and spaCy, we observed that some candidate domains in the set $\{d_1, d_2, \ldots, d_n\}$ were incorrect. This is because some entries and domains in IATE vocabulary do not seem to be semantically similar and are not reliable for annotation. For instance, the term "apply" is mapped to domain "AGRICULTURE, FORESTRY AND FISHERIES". The downloaded version of IATE dictionary did not include any context information to assist our dictionary lookup program for correct annotation of documents. Therefore, we filtered out such candidate entities by using Dexter [12], a Wikipedia entity linker.[7] The application of Dexter ψ on a document d produced a set of Wikipedia entities $\psi(d) = \{w_1, w_2, \ldots, w_n\}$. We used them to filter the subject domains $\{d_1, d_2, \ldots, d_n\}$, taking only the domains present in $\psi(d)$. Thus, we annotated all the documents in the corpus. In the next step, each document is transformed into a collection of <word, label> pairs as input for concept recognition system. In the <word, label> pair, *word* represents a word in the document, while *label* represents the IATE subjct domain or a spaCy NER tag associated with the word. In cases when *word* does not belong to any class, *label* is assigned to 'O' tag (concept or word does not belong to any subject domain).

3.2. Corpus Statistics

After generating the annotated corpus for both directives and SIs we divided each dataset into 80% training and 20% test set to build the concept recognition system. Table 1 shows the number of documents, tokens and vocabulary size for both directive and SI datasets respectively. We observe that SIs have a much larger vocabulary than directives. Table 2 shows the number of tokens labeled with IATE or spaCy tags or with a 'O' tag

Table 1. Number of documents, number of tokens and the vocabulary size (|V|) for directives (left) and SIs (right)

Dataset	# docs	# tokens	|V|
Train	2,307	4,646,286	24,522
Test	577	1,226,338	14,127
Total	2,884	5,872,624	38,649

Dataset	# docs	# tokens	|V|
Train	2,307	4,189,157	83,172
Test	577	1,096,246	33,757
Total	2,884	5,285,403	116,929

(tokens not belonging to any class). Table 3 represents the number of tagged tokens for each IATE subject domain and spaCY NER in train and test set of directive and statutory instruments.

Table 2. Number of tagged (IATE or spaCy tags) and untagged tokens (O tag).

	Directives		Statutory Instruments	
Dataset	IATE/spaCy Ner tags	O tag	IATE/spaCy Ner tags	O tag
Train	238,929	4,407,357	169,609	4,019,548
Test	64,678	1,161,660	45,854	1,050,392

[7] Wikipedia Entity Linkers find named entities in the text that can be linked to a Wikipedia page.

Table 3. Number of tagged tokens for IATE subject domains and named entities in directives and SIs corpus

IATE Subject Domains and spaCy Named Entities				
IATE Subject Domains	Directive Train	Directive Test	SI Train	SI Test
FINANCE	16,366	2,838	10,504	2,564
POLITICS	3,878	1,138	10,566	3,136
ENVIRONMENT	8,478	3,294	3,560	1,045
EDUCATION AND COMMUNICATIONS	13,419	4,066	9,936	3,340
LAW	55,366	13,767	37,851	8,240
INTERNATIONAL ORGANISATIONS	269	60	98	22
EMPLOYMENT AND WORKING CONDITIONS	4,069	922	7,033	1,399
AGRI-FOODSTUFFS	3,213	1,066	1,573	337
INDUSTRY	17,831	5,946	11,063	4,170
PRODUCTION, TECHNOLOGY AND RESEARCH	9,371	2,462	5,000	1,724
BUSINESS AND COMPETITION	18,356	4,047	9,405	3,027
ENERGY	9,585	2,515	2,599	590
TRANSPORT	12,402	2,964	11,181	3,223
EUROPEAN UNION	2,449	699	969	249
AGRICULTURE, FORESTRY AND FISHERIES	14,085	4,840	8,832	3,588
SOCIAL QUESTIONS	19,531	5,995	21,878	5,539
ECONOMICS	3,767	1,095	2,810	614
GEOGRAPHY	341	73	5,325	740
INTERNATIONAL RELATIONS	956	347	801	205
SCIENCE	6,214	1,575	2,943	773
TRADE	18,788	4,886	5,243	1,217
spaCy Named Entities	Directive Train	Directive Test	SI Train	SI Test
QUANTITY	4	0	4	5
MONEY	2	0	6	4
ORDINAL	1	0	2	2
TIME	106	22	46	16
DATE	81	61	381	85
O	4,407,357	1,161,660	4,019,548	1,050,392

3.3. *CRF-based Concept Recognition System*

The annotated corpus for both directives and SIs was divided into train (80%) and test (20%) sets to build and evaluate the concept recognition system. We utilized conditional random fields (CRFs) to build our concept recognition system as they have been known to work well in tasks which require labeling sequence data (especially natural language text). They are discriminative probabilistic models where each observation is a token from a sentence and the corresponding label (tag of subject domain or entity) represents the state sequence. We utilize the following features for our CRF model: word suffix, word identity, word shape, part-of-speech (POS) tag and some context information from the surrounding words. We used the Limited-memory BFGS training algorithm with L1+L2 regularization.

4. Results and Analysis

In this section, we present the results of our system. We evaluate our CRF-based concept recognition system with standard information retrieval metrics of precision, recall and F1-score. We did not consider accuracy as a fair metric for evaluation because in the training data we have very different number of mentions for each class. Thus, resulting in an unbalanced dataset. But we do present the precision, recall and F-score for each class of the concept recognition system. We carried out three runs of experiments to thoroughly evaluate the CRF concept recognition system:

- Directive Corpus (2884 documents): 80% train (2307 directives) and 20% test set (577 directives)
- SI Corpus (2884 documents) : 80% train (2307 SIs) and 20% test set (577 SIs)
- Combined Corpus (5768 documents) : 80% train (2307 directives + 2307 SIs) and 20% test set (577 directive + 577 SIs)

Table 4. Results (F1-score) for concept recognition for each class by CRF-based concept recognition system

Tag name	Directives	SIs	Directives + SIs
IATE Subject Domains			
FINANCE	0.68	0.62	0.62
POLITICS	0.70	0.74	0.71
ENVIRONMENT	0.68	0.41	0.66
EDUCATION AND COMMUNICATIONS	0.68	0.72	0.71
LAW	0.92	0.81	0.89
INTERNATIONAL ORGANISATIONS	0.52	0.14	0.32
EMPLOYMENT AND WORKING CONDITIONS	0.70	0.68	0.70
AGRI-FOODSTUFFS	0.75	0.73	0.68
INDUSTRY	0.67	0.45	0.60
PRODUCTION TECHNOLOGY AND RESEARCH	0.69	0.67	0.69
BUSINESS AND COMPETITION	0.78	0.77	0.77
ENERGY	0.81	0.50	0.74
TRANSPORT	0.59	0.60	0.58
EUROPEAN UNION	0.79	0.77	0.76
AGRICULTURE FORESTRY AND FISHERIES	0.70	0.58	0.64
SOCIAL QUESTIONS	0.68	0.65	0.66
ECONOMICS	0.66	0.57	0.68
GEOGRAPHY	0.52	0.76	0.75
INTERNATIONAL RELATIONS	0.70	0.59	0.59
SCIENCE	0.60	0.48	0.59
TRADE	0.77	0.66	0.76
spaCy Named Entities			
QUANTITY	0.00	0.00	0.00
MONEY	0.00	0.00	0.00
ORDINAL	0.00	0.00	0.00
TIME	0.62	0.00	0.60
DATE	0.00	0.19	0.47

Table 4 reports the F1-score of our CRF-based concept recognition model for each subject domain and entity class. We observe that all IATE subject domains are clearly distinguished due to the achievement of a reasonable F1 score for each domain for each corpus. The lower F1 score of domain 'INTERNATIONAL ORGANISATIONS' is explained by a smaller number of tagged tokens, resulting in only a few training instances (as observed from Table 3). The other subject domains had sufficient training data and therefore were classified with a higher F1 score. We also observe that CRF could not identify classes, 'QUANTITY','MONEY' and 'ORDINAL' of spaCY named entities because there were hardly any training instances for these classes (as observed from Table 3).'TIME' and 'DATE' classes also had very few training instances, thus resulting in a lower F1 score. These results also indicate that European and national legislation consists of very few named entities and are therefore more suited for concept recognition. The average F1 scores of our CRF-based concept recognition system for directive, SI and combined corpus were 0.75, 0.66 and 0.71 respectively (Table 5). The lower average F1 score for SI corpus is probably due to the larger vocabulary size of the SI corpus (Table 1). A larger vocabulary implies more diversity in the tokens assigned to each domain, thus also leading to fewer training instances. We also compare the performance of CRF with a baseline method (Most frequent class model). It is a simple model which

Table 5. Results of concept recognition with CRF model and comparison with baseline (Most Frequent Class) and Stanford NER model

Corpus	System	Precision	Recall	F1 score
Directive Corpus	Most frequent class	0.74	0.53	0.61
	CRF	0.80	0.71	0.75
	Stanford NER	0.80	0.71	0.75
SIs Corpus	Most frequent class	0.61	0.40	0.48
	CRF	0.73	0.61	0.66
	Stanford NER	0.68	0.53	0.59
Combined Corpus (Directives + SIs)	Most frequent class	0.66	0.47	0.54
	CRF	0.76	0.68	0.71
	Stanford NER	** (did not finish training)	**	**

computes the most frequent class assigned to each token in the training set, and it uses them to tag the new documents. If a word is not present in the training set, it assigns it to the class 'O'. We observe that CRF outperforms the baseline model. This is because the baseline model does not take into account the context information for a particular token while assigning it to a class. We also compared CRF with Stanford NER for both the Directive Corpus and SIs corpus. The CRF model had similar performance to Stanford NER in the directive corpus. However it outperformed the Stanford NER in the SIs corpus by achieving a higher F1-score. For the combined corpus, the Stanford NER was still in training and we could not record the results in time. These runs are indicated by ** in Table 5. We hope to record them for comparison in future work. One of the drawbacks of Stanford NER is the large amount of training time required (several days). The CRF-based concept recognition system utilizes few important features and completes training under an hour.

4.1. Discussion

In this section, we discuss the advantages of developing and training a CRF over using a dictionary lookup program to automatically detect concepts. One drawback of using dictionary tagging to annotate corpus is that some terms are missed and not tagged due to inconsistent rules to accommodate different phrases or tokenization errors. Also since the downloaded IATE dictionary did not provide any context information, we could not utilize context information to assign the correct tag to a particular token in the corpus. CRFs on the other hand, use contextual information to learn and assign tags because of their Markov property. Therefore, CRF models have the potential to reduce false positives and false negatives in the dictionary lookup tagging. In IATE dictionary, an entry, 'integrated energy performance' is linked to subject domain, 'INDUSTRY'. Table 7 presents an example sentence with tagged labels of IATE dictionary and predicted CRF labels. CRF classifies both 'energy' and 'performance' to 'INDUSTRY' subject domain whereas dictionary missed them. This is because dictionary lookup utilizes state-of-the-art tokenizers which are not 100% accurate and may lead to incorrect tokenization resulting in a mismatch. Most other multi-worded phrases like 'national regulatory authority', 'Federal Motor Transport Authority' and several others were tagged correctly by dictionary. CRF on the other hand, had some training instances (as shown in Table 6) from which it learns that terms 'energy' and 'performance' are related to 'INDUSTRY'. Thus it was able to correctly classify them. Thus, training a CRF model is advantageous also on automatically annotated corpora because it can improve the tagging of dictionary by learning these semantic relations between terms and subject domains. Thus, it can be

Table 6. Relevant training instances for CRF

Terms	IATE subject domains
seasonal energy performance ratio	INDUSTRY
energy performance diagnosis	INDUSTRY

used to improve the quality of annotations and develop a better gold standard for further work.

Table 8 shows an example phrase from the SI corpus to compare the performance of CRF with the Most frequent class model, Stanford NER and the true labels (from the dictionary). The label 'EMP' here refers to the subject domain, 'EMPLOYMENT AND WORKING CONDITIONS' from the IATE dictionary. We observe that CRF correctly classifies all of the labels. The Most frequent class (baseline) model could classify only word 'sick' correctly and missed out on 'statutory' and 'pay'. This is because in the training set there only few instances of words 'statutory' and 'pay' for 'EMP' class and most instances are for 'O' class. The term 'statutory' had 324 instances of 'O' class while only 31 instances of 'EMP' class. Therefore 'O' class was the most frequent class. We also observe that Stanford NER correctly classified 'statutory' and 'sick'. However, the words 'the' and 'pay' were incorrectly classified. Though, Stanford NER also utilizes a CRF model but the default model does not use part-of-speech (POS) tags. The knowledge of POS tags could have avoided the assignment of 'the' to 'EMP' class. The CRF model we implemented utilized POS tags as a feature (as mentioned towards the end of Section 3.3)

Table 7. Comparison of CRF output with the dictionary tagging

	CRF predicted labels	Dictionary
The	O	O
general	O	O
framework	O	O
for	O	O
a	O	O
methodology	ECONOMICS	ECONOMICS
of	O	O
calculation	O	O
of	O	O
the	O	O
integrated	O	O
energy	**INDUSTRY**	**O**
performance	**INDUSTRY**	**O**
of	O	O
buildings	O	O

Table 8. An example phrase to compare different models against the true values

	Most frequent class	Stanford NER	CRF	True Labels
the	O	EMP	O	O
statutory	O	EMP	EMP	EMP
sick	EMP	EMP	EMP	EMP
pay	O	O	EMP	EMP
up	O	O	O	O

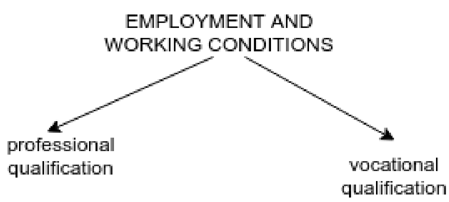
5. Alignment of similar terms across directive and SIs

In order to utilize the concept recognition system, it is important to align similar terms across European and national law. This semantic alignment of terms is highly useful for legal professionals to understand the differences in terminologies at the European and national level. It is also beneficial for development of other legal information systems which utilize this semantic information. The concept recognition system tags each term in the text to a particular subject domain. As a result we have a large collection of terms under each subject domain from both directives and statutory instruments. We divided the terms under each subject domain into two lists : directive terms and SI terms. We computed the set difference of these two lists to obtain a list of terms present in directive but not in SIs. Similarly, we also obtained a list of terms present in SIs but not in directives. Then we computed text similarity (using Levenshtein distance) to find the most semantically similar term in SIs (not present in directive) for a particular term in directive. Table 9 shows a few examples of such terms. Figure 1 shows the first example from Table 9. In future work, we intend to use the mapping of such terms to extend our text similarity system of detecting transposing provisions for EU directives [11].

Table 9. Aligned terms from European and national law

Subject Domain	Aligned terms (*Directive*→*SIs*)
EMPLOYMENT AND WORKING CONDITIONS	*professional qualification→vocational qualification* *seniority→job security* *occupational disease→industrial disease*
FINANCE	*life assurance→endowment assurance* *financial institution→financial administration* *dividend→tax on dividends*

Figure 1. An example of aligned terms under the same subject domain (Employment and Working Conditions): professional qualification (from directives) and vocational qualification (from SIs)



6. Conclusion and Future Work

In this paper, we developed and evaluated a CRF-based concept recognition system for European and national law. We generated a labeled corpus of directives and statutory instruments with subject domains of IATE vocabulary, Wikipedia and a state-of-the-art named entity recognition system. We evaluated the system on both European and national law corpus and analyzed its performance with respect to a baseline model and Stanford NER. Our results indicate that the concept recognition system is able to identify concepts in both directives and UK statutory instruments with a F1 score of 0.71 over the combined corpus. It can also be used to iteratively improve the dictionary lookup tagging from IATE.. We also demonstrated that concept recognition systems are useful to align legal terminology at European and national level to assist legal practitioners and domain experts. In future work, we intend to extend our current work to develop a multilingual model. We also plan to achieve a more fine-grained and hierarchical concept recognition by addition of sub-domains from EuroVoc or IATE.

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