CEUR-WS.org/Vol-2690/COUrT-paper2.pdf

The LATO Knowledge Model for Automated Knowledge Extraction and Enrichment from Court Decisions Corpora

Silvana Castano[1], Mattia Falduti[1], Alfio Ferrara[1], and Stefano Montanelli[1]

Università degli Studi di Milano
Department of Computer Science - Via Celoria, 18 - 20133 Milano
{silvana.castano,mattia.falduti,alfio.ferrara,stefano.montanelli}@unimi.it

Abstract. Knowledge extraction systems are strongly demanded in the legal domain, to provide legal actors like judges or lawyers with useful and relevant information to enforce a knowledge-based evaluation and judgement of new cases. In this paper, we present LATO-KM, a three-layer legal knowledge model where terms featuring legal knowledge, both law and case-law, are properly formalized as entities and relationships and they are implemented in the LATO ontology using SKOS. The LATO ontology constitutes the core component of CRIKE (CRIme Knowledge Extraction), a data-science approach and related tool environment conceived to support legal knowledge extraction and enrichment from a corpus of Court Decision documents.

Keywords: Legal Knowledge Model · Legal Ontology · Knowledge Extraction · Knowledge Enrichment

1 Introduction

Law is the set of rules which govern human conduct. Law is stated using a general and abstract terminology, in that it has to be applicable to several cases and events. On the opposite, Court Decisions (CDs) are written using specific and concrete terminology, in that they provide a contextualized, case-oriented interpretation of law deriving from the way judges/lawyers decide to apply the law statements to the specific circumstances/situation of the case at hand. Both law and case-law (that is, the set of CDs) constitute prominent knowledge sources to be considered for the knowledge-based evaluation and judgement of a new case, in that they provide the general legal framework (law) and the specific interpretations (case-law) adopted for already processed cases. When a new case is received for judgement, the knowledge-based evaluation process takes into account relevant *legal knowledge* to support CD definition, that is, knowledge deriving from

Copyright © 2020 for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0). This volume is published and copyrighted by its editors. *COUrT - CAiSE for Legal Documents*, June 9, 2020, Virtual Workshop.

i) the law, for understanding the general rules that are relevant/prominent for the current case [9, 12], and ii) the case-law, for detecting possible relevant interpretations of law terminology in history of similar CDs [15, 16]. In this context, automated legal knowledge extraction systems are strongly demanded, to support annotation of legal documents as well as legal knowledge extraction from them, to provide legal actors (e.g., judges, lawyers) with useful and relevant suggestions for managing incoming new cases [11]. In the literature, some contributions are appearing [1, 8]. In [14], the authors propose to combine Natural Language Processing (NLP) and machine learning techniques for mining relevant legal terms from documents. The LUIMA approach characterized by sentence-level annotations and reranking techniques has been also proposed to enforce retrieval over a CD dataset [4]. Moreover, a particularly relevant contribution is provided in [13] about extraction of case law sentences for argumentation of statutory terms. However, the accuracy of the above solutions depends on the completeness of the term-sets associated with concepts. Due to the variety of terminology adopted by judges in legal documents such as Court Decisions, the construction of accurate and complete term-sets to associate with concepts is really hard to obtain. Moreover, a challenging issue for effective legal knowledge extraction is related to the capability of developing knowledge models and related ontology tools where to link the general and abstract knowledge, as it is expressed by law terminology in law texts, with specific and concrete knowledge as it is expressed in CD texts. In fact, the task of discovering where and how law abstract terms have been applied by judges inside Court Decisions is currently performed by human experts and it is a time-consuming activity in most cases [3].

In this paper, we present LATO-KM (Legal Abstract Term Ontology - Knowledge Model), a three-layer knowledge model where terms featuring legal knowledge, both law and case-law, are properly formalized as entities and relationships and they are implemented in a LATO ontology using SKOS. The LATO-KM and the related LATO ontology constitute a core component of CRIKE (CRIme Knowledge Extraction), a data-science approach and related tool environment conceived to support knowledge extraction and enrichment from a corpus of Court Decision documents. Knowledge extraction in CRIKE is based on multi-label classification techniques that aim at associating CD documents with appropriate concepts in the LATO ontology. Knowledge enrichment in CRIKE is based on black-box model explanation techniques that aim at selecting the document features (i.e., terms) candidate for enrichment of the LATO ontology.

The paper is organized as follows. Section 2 presents the LATO ontology formalization. The CRIKE techniques for knowledge extraction and enrichment are described in Section 3. In Section 4, we discuss experimental results on a real CD dataset. Concluding remarks are finally provided in Section 5.

2 The LATO legal knowledge model

The legal knowledge model of LATO captures and formalizes the features and nature of terminology used in law and case-law documents. A design challenge is to find a suitable way of modeling the different nature of terms appearing in law and case law as well as their meaning and roles [2]. To model legal knowledge and capture these requirements, we define LATO-KM, a three-layer knowledge model based on the following entities and relationships (see Fig. 1):

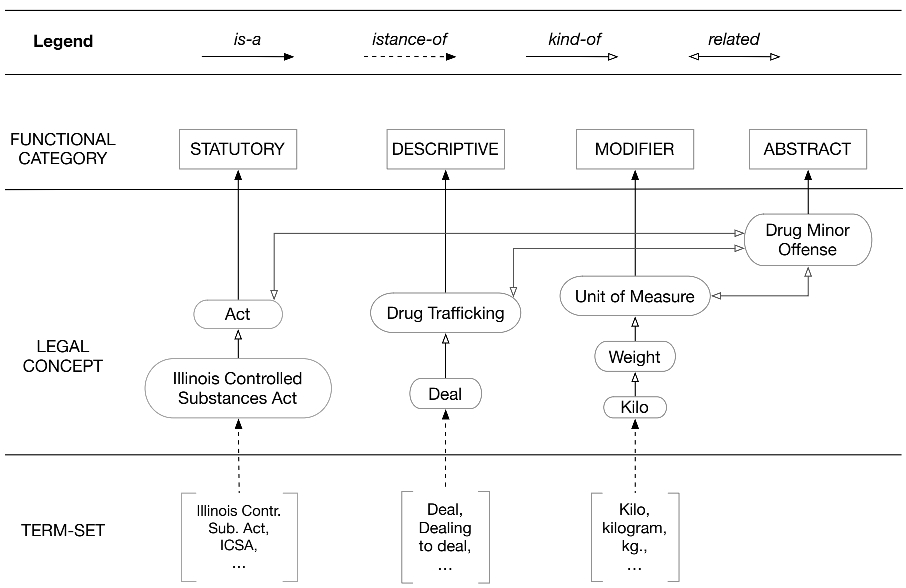

Fig. 1. Overview of LATO-KM with an example of legal knowledge modeling about drug crimes

- *Legal concept*: a legal concept C_i denotes a general rule/fact/element defined in the law (e.g., *Act*, *Illinois Controlled Substances Act*) and it is labelled with the terminology that appears in law texts. Legal concepts constitute the intermediate layer of LATO-KM.
- *Term-set*: a term-set T_i represents the concrete interpretation of a legal concept C_i in form of a set of terms occurrences that can be found in case-law texts. A term in a term-set is a string of characters of the language of the case law texts; also multi-term expressions are considered as terms in LATO (e.g. both *Illinois Contr. Sub. Act* and the acronym *ICSA* are terms). Term-sets constitute the bottom layer of LATO-KM.
- *Functional category*: a functional category represents the different kinds/roles of legal concepts in the law formulation, namely descriptive, statutory, modifier, and abstract, respectively. A **statutory category** describes a legal

concept featuring something that is directly or indirectly defined in the law specification itself (e.g., *Act*). A **descriptive category** describes a legal concept featuring actions, human activities, and any real-life object in the law specification (e.g., *Drug Trafficking*). A **modifier category** describes a legal concept featuring quantitative/qualitative aspects of things/actions in the law specification (e.g., *Weight*). An **abstract category** describes a legal concept featuring something indeterminate that requires a concrete application for being really defined (e.g., *Drug Minor Offence*) [2]. Functional categories constitute the top layer of LATO-KM.

According to LATO-KM, the concrete meaning of legal concepts is fully defined by referring to the specific terminology (i.e., term-set) that appears in real CDs. Moreover, legal concepts are classified with respect to the role they play in the law formulation using functional categories. To formalize, a legal concept C_i is defined as 3-uple of the form:

$$C_i = \langle n(C_i), \mathbb{C}(C_i), T_i^* \rangle$$

where:

- $n(C_i)$ is the label of the legal concept;
- $\mathbb{C}(C_i) \in \{SC, DC, MC, AC\}$ is the functional category of C_i, either statutory (SC), descriptive (DC), modifier (MC), or abstract (AC).
- $T_i^* = \{t_1, \ldots, t_n\}$ is the term-set of the concept C_i, namely the language terms concretely used in legal document corpora (i.e., Court Decisions) to refer to C_i. The asterisk symbol ("*") denotes optionality, in that we may have some legal concepts not yet associated with a corresponding term-set. For instance, abstract concepts are not directly associated with a specific term-set, but rather they are indirectly expressed through the term-sets associated with the legal concepts to which the abstract concept is related.

Intra- and inter-layer relationships are defined in LATO-KM to capture the semantic relationships that hold between pairs of entities. The following intra-layer binary relationships are defined in LATO-KM:

- **Term-to-Term**: it is a binary relationship between a pair of terms t and t' in a term-set T_i at the bottom layer, that holds due to either a morphological or a linguistic relationship between terms. Examples of morphological relationships are:
  - paradigm (e.g. *to deal - dealt - dealt*)
  - conjugation for verb (e.g. *dealt - deals - dealing*)
  - declension for nouns (e.g. *drug - drugs - drug's*)
  - abbreviation (e.g. *Illinois Contr. Sub. Act - ICSA*)
  - string similarity (e.g. *Substances Act - substances act - Subs. Act*).

  An example of linguistic relationship is synonymy (e.g., *Paragraph - Section*).

- **Concept-to-Concept**: it is a binary relationship between two legal concepts C_i and C_j at the intermediate layer, capturing semantic relationships holding between them in the law formulation. In particular, we introduce the kind-of relationship between two concepts to represent a generalization/specialization relationship between them. For example, *Drug minor offence* kind-of *Minor offence* is defined to express the fact that the former is a more specific crime than the latter in the law. Moreover, we introduce the related relationship between two concepts to represent a generic positive relationship between them. For example, *Drug Minor Offence* related *Drug* is defined to express the fact that the crime of drug minor offence involves detention of drug in some quantity.

The following inter-layer binary relationships are defined in LATO-KM:

- **Term-to-Concept**: it is a binary relationship between a term $t \in T_i$ and a legal concept C_i denoting that C_i can be "lexicalized" by t in a CD text. A Term-to-Concept relationship is defined through the instance-of relationship for each term $t \in T_i$ and the corresponding legal concept C_i at the intermediate layer of LATO-KM. For example, *ICSA* instance-of *Illinois Controlled Substances Act* is defined to express the term *ICSA* belongs to the term-set of the concept *Illinois Controlled Substances Act*.
- **Concept-to-Category**: it is a binary relationship between a legal concept C_i and a functional category $\mathbb{C}$ (C_i) expressing the nature of the concept in the law formulation. A Concept-to-Category relationship is defined through the is-a relationship. *Act* is-a *Statutory* is defined to express that the notion of *Act* is directly defined in the law.

2.1 The LATO ontology structure

The LATO-KM is implemented in a LATO ontology by using the Simple Knowledge Organization System (SKOS) [6]. Table 2.1 provides a summary view of the SKOS concepts and relations used in the LATO ontology to implement entities and relationships of the LATO-KM (see Fig. 1).

The legal concepts of the intermediate layer are implemented as SKOS concepts in LATO. Concept-to-Concept relationships are specified through a corresponding SKOS relation. In particular, the kind-of relationship of LATO-KM is specified through the skos:broader relation. For instance, a skos:broader relation is defined between the concept Cocaine and the concept Drug. The Related relationship of LATO-KM is specified through the skos:related relation. For instance, a skos:related relation is defined between the concept Drug Minor Offence and the concept Drug.

The term-sets of the bottom layer are implemented using labels of SKOS concepts. In particular, for each SKOS concept i) a skos:prefLabel is defined to implement the instance-of relationship, and ii) a number of skos:altLabel are defined to implement the various Term-to-Term relationships denoting possible alternative terms for the considered SKOS concept. For instance, a skos:prefLabel

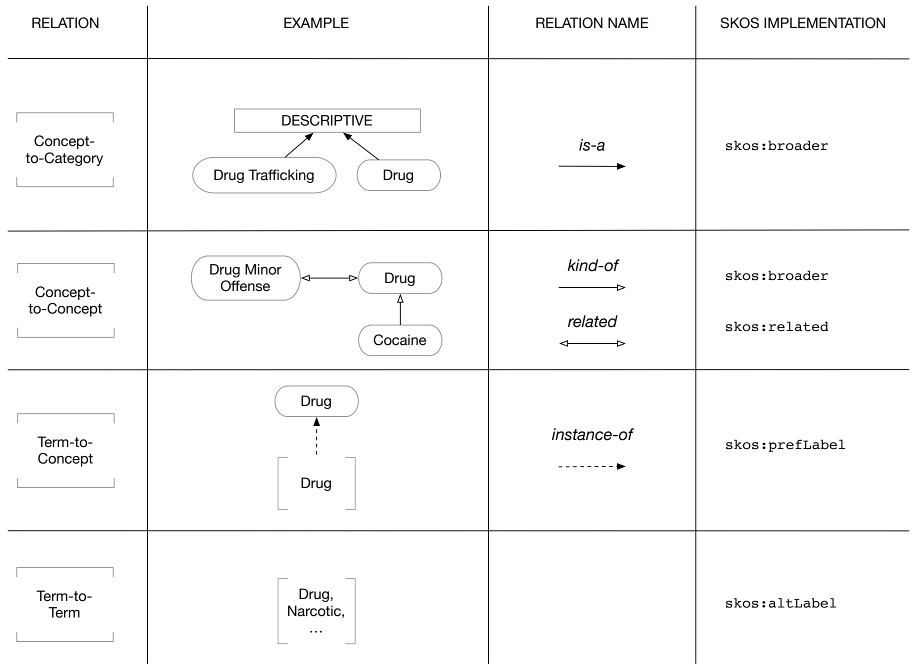

Fig. 2. SKOS concepts and relations of the LATO ontology

relation is defined between the Drug LATO concept and the Drug term, while a skos:altLabel relation is defined between the Drug term and the Narcotics term.

Finally, functional categories of the top layer are implemented as SKOS concepts, too. Concept-to-Category is-a relationships are expressed through the skos:broader relation. For instance, a skos:broader relation is defined between the Drug LATO concept and the Descriptive category concept.

3 Knowledge extraction and enrichment in CRIKE

The LATO ontology is a core component of the CRIKE approach to enforce knowledge extraction and enrichment based on a given corpus of Court Decision documents (see Figure 3). The goal of CRIKE is to progressively enrich the knowledge specified in a reference LATO ontology by extracting concrete terminology associated with concept applications/interpretations occurring in the considered document corpus. At the beginning, CRIKE relies on an initial version of the LATO ontology where domain experts manually define a starting set of legal concepts of interest with associated term-sets. CRIKE is enforced as a cyclic incremental approach where the execution of knowledge extraction and knowledge enrichment tasks produces a new enriched version of the LATO ontology. The enrichment task consists in discovering terms to populate term-sets

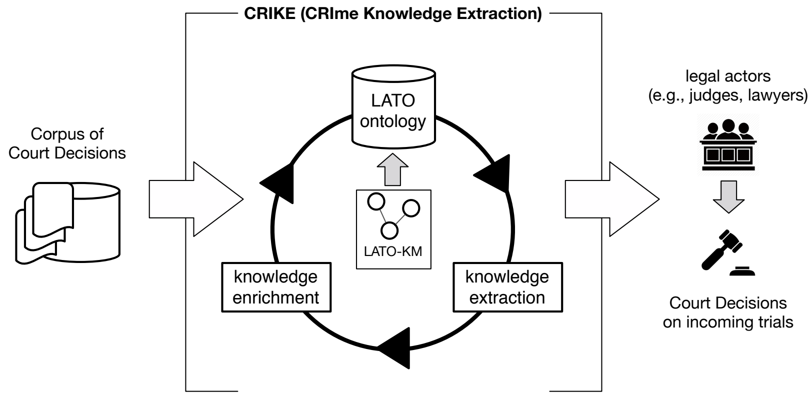

Fig. 3. The CRIKE approach to knowledge extraction and enrichment

of legal concepts that have recognized in the text of the CD documents. This new ontology version is then exploited to trigger the execution of a new CRIKE cycle to further enrich the LATO ontology. The enforcement of CRIKE cycles is stopped when the enrichment of the LATO ontology is terminated, namely when it is not possible to detect/extract additional terms to insert in the LATO ontology. As a result, the knowledge currently-available in the LATO ontology can be exploited to support legal actors such as judges and lawyers in managing new incoming legal trials and taking appropriate Court Decisions.

3.1 Knowledge extraction

Knowledge extraction in CRIKE is based on multi-label classification techniques where the training set is built by relying on the ontology contents without the need of manual annotation. In other words, CRIKE works as a sort of self-training scheme that can be considered as a kind of semi-supervised learning approach. Extraction is articulated in three main steps as follows:

Document annotation. For each CD document d, the goal of annotation is to determine the set of associated legal concepts $\mathcal{C}_d$ as follows:

$$\mathcal{C}_d = \left\{ C_i : \left[\sum_{t \in T_i} w(t,d) \right] \geq th \right\}$$

where $w(t,d)$ is the weight of a term t in the document d according to standard information retrieval techniques based on tokenization and tf-idf, while th is a threshold used to set the minimum cumulative weight of all the terms $t \in T_i$ that is required for associating a corresponding concept C_i with the document d.

Document vector representation. For each document d in the corpus, a vector-based representation $\boldsymbol{d}$ is derived by exploiting `doc2vec` techniques [7]. In particular, doc2vec is based on an unsupervised algorithm that learns fixed-length feature representations from variable-length pieces of texts (e.g., documents). The algorithm represents each document by a dense vector which is trained to predict words in the document. In addition, each document vector $\boldsymbol{d}$ is associated with a *concept vector* $\boldsymbol{c}_d$, where each vector dimension denotes a concept C_i in the LATO ontology whose value is set to 1 if $C_i \in \mathcal{C}_d$, or it is set to 0 otherwise.

Document classification. A multi-label classifier is employed to generate a model that is capable to predict the association of CD documents with legal concepts. In CRIKE, we employ a Convolutional Neural Network (CNN) with the goal to generalize the terminology of the documents and to enable the association of legal concepts with Court Decisions that actually contain terms other than those already included in LATO. For each document d, the CNN receives the document vector representation $\boldsymbol{d}$ as input and it produces the corresponding concept vector representation $\boldsymbol{c}_d$ as output. As a result, a multi-label classification model M is generated to map the correspondence between corpus documents and legal concepts in the LATO ontology. In particular, by $C_i \in M(d)$ we denote that the document d is associated with the legal concept C_i through the model M.

3.2 Knowledge enrichment

Knowledge enrichment in CRIKE is based on black-box model explanation techniques that aim at selecting the document features (i.e., terms) that play a major role in determining the decision of the CNN classifier (see above the knowledge extraction step) about the association of concepts with the corpus documents. The selected document features are candidate for the enrichment of the LATO ontology. Enrichment is articulated in three main steps as follows:

Classification explanation. Black-box model explanation is enforced by relying on LIME (Local Interpretable Model-agnostic Explanations) [10]. LIME has been proposed to provide local explanations of black-box models, which means to explain why (i.e., due to which features) a black-box model decides to assign a given class to a certain document [5]. According to the classification model M generated by the CNN, LIME calculates a score $\eta(t, d)$ for each term $t \in d$, where $\eta(t, d)$ is directly proportional to the importance of t in determining the model decision $C_i \in M(d)$. Moreover, we exploit LIME to extend the black-box model explanation to the concept layer of LATO as follows. Given a concept C_i, we consider all the documents $D_{C_i} = \{d : C_i \in M(d)\}$ and all the terminology that is potentially relevant for C_i, that is:

$$T_{C_i} = \left\{ t : t \in \bigcup_{d \in D_{C_i}} d \right\}$$

The choice of CNN is due to the positive experimental results we observed in a number of considered case-studies. As a general remark, different kinds of multi-label classifier can be employed for enforcing document classification, like for example random forest and kNN.

Then, we associate each term $t \in T_{C_i}$ with a degree of relevance $\eta_{C_i}(t)$ as follows:

$$\eta_{C_i}(t) = \sum_{t \in T_{C_i}} \sum_{d \in D_{C_i}} \eta(t, d)$$

The set T_{C_i} is the set which contains the terms that are candidate to enrich the term-set associated with C_i in LATO.

Expert validation. For each concept C_i, legal experts are involved to validate the terms in the set $T_{C_i} \setminus T_i$. Furthermore, the legal experts define the set $R_i \subseteq (T_{C_i} \setminus T_i)$ containing the terms that are relevant for C_i. In the validation step, the degree of relevance $\eta_{C_i}(t)$ is exploited by the experts i) to filter out terms whose association with the concept C_i is poor (i.e., low values of $\eta_{C_i}(t)$), and ii) to select terms whose association with the concept C_i is strong (i.e., high values of $\eta_{C_i}(t)$).

Ontology enrichment. According to the results of legal expert validation, the term-set T_i associated with each concept C_i is enriched. Being k the current CRIKE cycle, enrichment is enforced as follows:

$$T_i^{k+1} \equiv T_i^k \cup R_i$$

where T_i^k is the term-set initially associated with the concept C_i and T_i^{k+1} is the term-set associated with C_i after enrichment.

Example. In Figure 4, we report an example of two court decision fragments, d_1 and d_2 that are associated with the legal concept Drug.

> d_1: [...] *Paragraph 14 of section 1 of the same act provides: "***Narcotic Drugs** *means* <u>*coca leaves*</u>*,* <u>*opium*</u>*,* **cannabis***, and each substance neither chemically nor physically distinguishable from them."* [...]
>
> d_2: [...]*Defendant, who was charged by indictment with violation of 402 of the Illinois* <u>*Controlled Substances*</u> *Act"* [...]

Fig. 4. Example of CD document sentences associated with the legal concept Drug

The Court Decision d_1 is included in the corpus used for training the multi-label classification model M. The model classify both d_1 and d_2 as documents related to the Drug legal concept. In case of d_1, the choice of the classifier is trivial, since d_1 is classified as Drug-related in the training set and it contains the terms narcotic drugs and cannabis. The decision of classifying d_2 as a Drug-related is instead less trivial, because d_2 does not contain any of the terms provided by experts as part of the term-set of the Drug concept. However, the two documents are semantically similar. As a consequence, the two court decisions are close enough in the feature (i.e., term) space to motivate the classifier decision of associating both with the concept Drug. Thus, we can use LIME to detect the terms of d_1 and d_2 that have the main impact on the classifier decision, namely

Table 1. Term-sets used for the evaluation

Legal Concept	Term-Set	Size
drug	narcotic, cocaine, crack, [...]	15
drug trafficking verbs	drug trafficking, drug sale, drug use, [...]	18
unit of measure	gram, grams, gr., [...]	10
illinois legislation	720 ILCS 570, Illinois Controlled Substances Act, Drug Abuse Control Act, [...]	6
criminal procedure	arrest, arrested, seizure, [...]	7
evidence	plastic bag, plastic bags, paraphernalia	3

the terms that, if deleted from the court decision, may more likely produce a different classification result. According to the LIME results, we obtain the following terms for the concept Drug: narcotic drugs, controlled substances, cannabis, coca leaves, opium. Among the list, narcotic drugs and cannabis are already present in LATO, while the others (underlined in Figure 4) are validated by the legal experts and included in an enriched version of the term-set layer of LATO.

4 Experimental results

The goal of our experimentation is to assess the capability of our approach to discover new terms for enriching the term-sets of legal concepts in LATO. For the experiments, we select six concepts from our legal ontology, namely drug, drug trafficking, unit of measure, illinois legislation, criminal procedure, and evidence. These concepts are all related to the drug criminal legislation of the State of Illinois. The court decision corpus used for experiments is composed by 14,000,000 sentences taken from about 180,000 decisions of courts of the State of Illinois taken from the Caselaw Access Project (CAP) that provides public access to U.S. law (`https://case.law/bulk/download`) digitized from the collection of the Harvard Law Library. Sentences are indexed by exploiting standard techniques for tokenization and compound term detection. The initial term-sets associated with the selected concepts have been manually defined by a legal expert and they are shown in Table 1.

By using CRIKE, we select a subset of 115,993 court decision sentences that constitutes the training set for the classification step. The training set is prepared for classification by embedding each document in a 100 dimensions vector using doc2vec to obtain a $115{,}993 \times 100$ corpus matrix. The six concepts selected for the experiment are associated with CD documents with the document annotation process discussed in Section 3. The model M used to train the classifier is a neural network organized in three layers. Between the input and the output layer, we use a convolution filter activated by ReLU. The M_1 accuracy obtained by cross-validation is 0.77. M is then used to perform terminology enrichment using LIME. For each legal concept C_i, we obtain a new set of terms T_{C_i}, where each term t is associated with the degree of relevance $\eta_{C_i}(t)$. In the experiment, a legal expert validated the top-20 terms in the new term-set T_i of each concept C_i. In particular, the expert associates each term t with a numerical value in

Table 2. Results of knowledge enrichment

	drug	drug trafficking	unit of measure	illinois legislation	criminal procedure	evidence	**total**
$\mid T_{C_i} \mid$	20	20	20	20	20	20	**120**
$\mid T^{-1} \mid$	1	0	3	1	6	10	**21**
$\mid T^{0} \mid$	14	17	10	6	6	3	**65**
$\mid T^{1} \mid$	5	3	7	13	8	7	**34**
$\frac{(\lvert T^0\rvert+\lvert T^1\rvert)}{\lvert T_{C_i}\rvert}$	0.95	1.0	0.85	0.95	0.75	0.4	**0.83**
$\frac{\lvert T^1\rvert}{(\lvert T^0\rvert+\lvert T^1\rvert)}$	0.26	0.15	0.42	0.68	0.57	0.7	**0.34**

$\{-1, 0, 1\}$, where T^{-1} denotes the set of terms that were not in LATO and that are not relevant for the concept C_i; T^0 denotes the set of terms that were in LATO (and thus have been already validated as relevant); T^1 denotes the set of terms that were not in LATO but that are relevant for the concept C_i. An overview of the results of knowledge enrichment is shown in Table 2.

The number of relevant terms retrieved through knowledge enrichment (i.e., terms in T^0 or T^1) is equal to the 83% of the total number of new terms validated by the expert (T_{C_i}). The 34% of those terms was not in the term-sets of LATO. As expected, the increment of new relevant terms is higher for the concepts that were associated with small term-sets, such as illinois legislation, criminal procedure, and evidence. The number of irrelevant terms T^{-1} is limited with the exception of the concept evidence, because the criminal evidences usually consist in common objects that are used in a criminal context. These objects are thus associated with a generic terminology (e.g., garbage, suitcase) that cannot be associated per se to an evidence according to the legal expert. The new relevant terms are finally included in the term-sets of LATO. A new CRIKE cycle has been then executed. The new term-sets are exploited in the knowledge extraction steps and a new training set of 158,398 CD sentences is extracted (+37% with respect to the first execution). These sentences are then used to train a new model M and to enforce the execution of the knowledge enrichment steps. Finally, the accuracy of M obtained by cross-validation is 0.81 (+5.2%).

5 Concluding remarks

In this paper, we presented the LATO-KM for automated knowledge extraction from Court Decisions corpora. The CRIKE knowledge extraction and enrichment process is based on black-box models explanation techniques. Preliminary results on a corpus of Court Decision documents show that our approach achieves promising results in effectively discovering new terminology for enriching the term-sets associated with legal concepts in the LATO ontology. Ongoing work is related to the extension of the LATO knowledge model to enforce rule-based extraction and classification techniques. The goal is to improve the accuracy in recognizing the application of abstract legal concepts in CD documents. We aim to exploit reasoning techniques based on ontology rules defined over legal concepts for detecting concept instances throughout documents where specific constraints are satisfied.

References

1. Ashley, K.D.: Artificial Intelligence and Legal Analytics: New Tools for Law Practice in the Digital Age. Cambridge University Press (2017)
2. Castano, S., Falduti, M., Ferrara, A., Montanelli, S.: Crime Knowledge Extraction: An Ontology-Driven Approach for Detecting Abstract Terms in Case Law Decisions. In: Proc. of the 17th Int. Conf. on Artificial Intelligence and Law (2019)
3. Grabmair, M., Ashley, K.D.: Facilitating Case Comparison Using Value Judgments and Intermediate Legal Concepts. In: Proc. of the 13th Int. Conference on Artificial Intelligence and Law. pp. 161–170. ACM (2011)
4. Grabmair, M., Ashley, K.D., Chen, R., Sureshkumar, P., Wang, C., Nyberg, E., Walker, V.R.: Introducing LUIMA: an Experiment in Legal Conceptual Retrieval of Vaccine Injury Decisions Using a UIMA Type System and Tools. In: Proc. of the 15th Int. Conference on Artificial Intelligence and Law. pp. 69–78. ACM (2015)
5. Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., Pedreschi, D.: A Survey of Methods for Explaining Black Box Models. ACM Computing Surveys (CSUR) 51(5), 1–42 (2018)
6. Isaac, A., Summers, E.: SKOS Simple Knowledge Organization System Primer. Tech. rep., Working Group Note, W3C (2009)
7. Le, Q., Mikolov, T.: Distributed Representations of Sentences and Documents. In: Proc. of the 31st Int. Conference on Machine Learning (2014)
8. Nazarenko, A., Wyner, A.: Legal NLP Introduction. Traitement Automatique des Langues 58(2), 7–19 (2017)
9. Poudyal, P.: A machine learning approach to argument mining in legal documents. In: Proc. of the Int. Workshop on AI Approaches to the Complexity of Legal Systems (2018)
10. Ribeiro, M.T., Singh, S., Guestrin, C.: "Why Should I Trust You?" Explaining the Predictions of Any Classifier. In: Proc. of the 22nd ACM SIGKDD Int. Conference on Knowledge Discovery and Data Mining. pp. 1135–1144 (2016)
11. Rossi, A., Ducato, R., Haapio, H., Passera, S., Palmirani, M.: Legal Design Patterns: Towards a New Language for Legal Information Design. In: Proc. of the 22nd Int. Legal Informatics Symposium (2019)
12. Sartor, G., Casanovas, P., Biasiotti, M., Fernández-Barrera, M.: Approaches to Legal Ontologies: Theories, Domains, Methodologies, vol. 1. Springer Science & Business Media (2010)
13. Savelka, J., Ashley, K.D.: Extracting Case Law Sentences for Argumentation about the Meaning of Statutory Terms. In: Proc. of the 3rd Int. Workshop on Argument Mining. pp. 50–59 (2016)
14. Savelka, J., Grabmair, M., Ashley, K.D.: Mining Information from Statutory Texts in Multi-Jurisdictional Settings. In: Proc. of the Int. Conference on Legal Knowledge and Information Systems. pp. 133–142. IOS Press (2014)
15. Thammaboosadee, S., Kiattisin, S., Darakorn, S., Watanapa, B.: Sentence Identification System based on Criminal Law Ontology. International Review of Law, Computers & Technology 31(3) (2017)
16. Wagh, R.S.: Knowledge Discovery from Legal Documents Dataset Using Text Mining Techniques. International Journal of Computer Applications 66(23) (2013)