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ORIGINAL RESEARCH

Unsupervised law article mining based on deep pre-trained language representation models with application to the Italian civil code

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Abstract

Modeling law search and retrieval as prediction problems has recently emerged as a predominant approach in law intelligence. Focusing on the law article retrieval task, we present a deep learning framework named LamBERTa, which is designed for civil-law codes, and specifically trained on the Italian civil code. To our knowledge, this is the first study proposing an advanced approach to law article prediction for the Italian legal system based on a BERT (Bidirectional Encoder Representations from Transformers) learning framework, which has recently attracted increased attention among deep learning approaches, showing outstanding effectiveness in several natural language processing and learning tasks. We define LamBERTa models by fine-tuning an Italian pre-trained BERT on the Italian civil code or its portions, for law article retrieval as a classification task. One key aspect of our LamBERTa framework is that we conceived it to address an extreme classification scenario, which is characterized by a high number of classes, the few-shot learning problem, and the lack of test query benchmarks for Italian legal prediction tasks. To solve such issues, we define different methods for the unsupervised labeling of the law articles, which can in principle be applied to any law article code system. We provide insights into the explainability and interpretability of our LamBERTa models, and we present an extensive experimental analysis over query sets of different type, for single-label as well as multi-label evaluation tasks. Empirical evidence has shown the effectiveness of LamBERTa, and also its superiority against widely used deep-learning text classifiers and a few-shot learner conceived for an attribute-aware prediction task.

Keywords Law article retrieval · Deep learning · Deep pre-trained language models · BERT · Text classification · Italian civil code

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1 Introduction

The general purpose of law search is to recognize legal authorities that are relevant to a question expressing a legal matter (Dadgostari et al. 2021). The interpretative uncertainty in law, particularly that related to the jurisprudential type which is capable of directly affecting citizens, has prompted many to model law search as a prediction problem (Dadgostari et al. 2021). Ultimately, this would allow lawyers and legal practitioners to explore the possibility of predicting the outcome of a judgment (e.g., the probable sentence relating to a specific case), through the aid of computational methods, also sometimes referred to as *predictive justice* (Viola 2017). Predictive justice is currently being developed, to a prevalent extent, following a statistical-jurisprudential approach: the jurisprudential precedents are verified and future decisions are predicted on their basis. However, as stated by legal professionals (Viola 2017), several reasons point out that this approach should not be preferred, because of its limited scope only to cases in which there are numerous precedents, so as to exclude unprecedented cases relating to new regulations, not yet subject to stratified jurisprudential guidelines. In fact, the jurisprudential approach is not in line with any *civil law* system—which is adopted in most European Union states and non-Anglophone countries in the world—with the consequence of a high risk of fallacy (i.e., repetition of errors based on precedents) and risk of standardization (i.e., if a lawsuit is contrary to many precedents, then no one will propose such a lawsuit).

Clearly, from a major perspective as a *data-driven artificial-intelligence* task, predicting judicial decisions is carried out exclusively based on the legal corpora available and the selected algorithms to use, as remarked by Medvedeva et al. (2020). Moreover, as also witnessed by an increased interest from the artificial intelligence and law research community, a key perspective in legal analysis and problem solving lays on the opportunities given by advanced, data-driven computational approaches based on natural language processing (NLP), data mining, and machine learning disciplines (Conrad and Branting 2018).

Predictive tasks in legal information systems have often been addressed as text classification problems, ranging from case classification and legal judgment prediction (Nallapati and Manning 2008; Liu and Hsieh 2006; Lin et al. 2012; Aletras et al. 2016; Sulea et al. 2017; Wang et al. 2018; Medvedeva et al. 2020), to legislation norm classification (Boella et al. 2011), and statute prediction (Liu et al. 2015). Early studies have focused on statistical textual features and machine learning methods, then the progress of *deep learning* methods for text classification (Goodfellow et al. 2016; Goldberg 2017) has prompted the development of deep neural network frameworks, such as recurrent neural networks, for single-task learning [e.g., charge prediction (Luo et al. 2017; Ye et al. 2018), sentence modality classification (O'Neill et al. 2017; Chalkidis et al. 2018), legal question answering (Do et al. 2017)] or even multi-task learning (e.g., Yang et al. (2019), Zhou et al. (2019)).

More recently, *deep pre-trained language models*, particularly the Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al. 2019), have emerged showing outstanding effectiveness in several NLP tasks. Thanks to their ability to learn a contextual language understanding model, these models overcome the need for feature engineering (upon which classic, sparse vectorial representation models rely). Nonetheless, since they are originally trained from generic domain corpora, they should not be directly applied to a specific domain corpus, as the distributional representation (embeddings) of their lexical units may significantly shift from the nuances and peculiarities expressed in domain-specific texts—and this certainly holds for the legal domain as well, where interpreting and relating documents is particularly challenging.

Developing BERT models for legal texts has very recently attracted increased attention, mostly concerning classification problems (e.g., Rabelo et al. 2019; Chalkidis et al. 2019a; Sanchez et al. 2020; Shao et al. 2020; Chalkidis et al. 2020; Yoshioka et al. 2021; Nguyen et al. 2021). Our research falls into this context, as we propose a BERT-based framework for law article retrieval based on civil-law-based corpora. More specifically, as we wanted to benefit from the essential consultation provided by law professionals in our country, our proposed framework is completely specified using the Italian Civil Code (ICC) as the target legal corpus. Notably, only few works have been developed for Italian BERT-based models, such as a retrained BERT for various NLP tasks on Italian tweets (Polignano et al. 2019), and a BERT-based masked-language model for spell correction (Puccinelli et al. 2019); however, *no study leveraging BERT for the Italian civil-law corpus has been proposed so far*.

Our main contributions in this work are summarized as follows:

- We push forward research on law document analysis for civil law systems, focusing on the modeling, learning and understanding of logically coherent corpora of law articles, using the Italian Civil Code as case in point.
- We study the law article retrieval task as a prediction problem based on the deep machine learning paradigm. More specifically, following the lastest advances in research on deep neural network models for text data, we propose a deep pre-trained contextualized language model framework, named LamBERTa (Law article mining based on BERT architecture). LamBERTa is designed to fine-tune an Italian pre-trained BERT on the ICC corpora for law article retrieval as prediction, i.e., given a natural language query, predict the most relevant ICC article(s).
- Notably, we deal with a very challenging prediction task, which is characterized not only by a high number (i.e., hundreds) of classes—as many as the number of articles—but also by the issues that arise from the need for building suitable training sets given the lack of test query benchmarks for Italian legal article retrieval/prediction tasks. This also leads to coping with few-shot learning issues (i.e., learning models to predict the correct class of instances when a small amount of examples are available in the training dataset), which has been recognized as one of the so-called *extreme classification* scenarios (Bengio et al. 2019; Chalkidis et al. 2019b). We design our LamBERTa framework to solve such issues based on different schemes of *unsupervised training-instance labeling* that we originally define for the ICC corpus, although they can easily be generalized to other law code systems.

- We address one crucial aspect that typically arises in deep/machine learning models, namely *explainability*, which is clearly of interest also in artificial intelligence and law (e.g., Branting et al. 2019; Hacker et al. 2020). In this regard, we investigate explainability of our LamBERTa models focusing on the understanding of how they form complex relationships between the textual tokens. We further provide insights into the patterns generated by LamBERTa models through a visual exploratory analysis of the learned representation embeddings.
- We present an extensive, quantitative experimental analysis of LamBERTa models by considering:
    - six different types of test queries, which vary by originating source, length and lexical characteristics, and include *comments* about the ICC articles as well as *case law decisions* from the civil section of the Italian Court of Cassation that contain significant jurisprudential sentences associated with the ICC articles;
    - *single-label* evaluation as well as *multi-label* evaluation tasks;
    - different sets of assessment criteria.

  The obtained results have shown the effectiveness of LamBERTa, and its superiority against (i) widely used deep-learning text classifiers that have been tested on our different query sets for the article prediction tasks, and against (ii) a few-shot learner conceived for an attribute-aware prediction task that we have newly designed based on the availability of ICC metadata.

The remainder of the paper is organized as follows. Section 2 overviews recent works that address legal classification and retrieval problems based on deep learning methods. Section 3 describes the ICC corpus, and Sect. 4 presents our proposed framework for the civil-law article retrieval problem. Sections 5 and 6 are devoted to qualitative investigations on the explainability and interpretability of LamBERTa models. Quantitative experimental evaluation methodology and results are instead presented in Sects. 7 and 8. Finally, Sect. 9 concludes the paper.

2 Related work

Our work belongs to the corpus of studies that reflect the recent revival of interest in the role that machine learning, particularly deep neural network models, can take on artificial intelligence applications for text data in a variety of domains, including the legal one. In this regard, here we overview recent research works that employ deep learning methods for addressing computational problems in the legal domain, with a focus on classification and retrieval tasks. Note that the latter are major categories for the data-driven legal analysis literature review, along with entailment and information extraction based on NLP approaches (e.g., named entity recognition, relation extraction, tagging), as extensively studied by Chalkidis and Kampas in Chalkidis and Kampas (2019), to which we refer the interested reader for a broader overview.

Most existing works on deep-learning-based law analysis exploit recurrent neural network models (RNNs) and convolutional neural networks (CNNs), along with the classic multi-layer perceptron (MLP). For instance, O'Neill et al. (2017) utilize all the above methods for classifying deontic modalities in regulatory texts, demonstrating superiority of neural network models over competitive classifiers including ensemble-based decision tree and largest margin classifiers. Focusing on obligation and prohibition extraction as a particular case of deontic sentence classification, Chalkidis et al. (2018) show the benefits of employing a hierarchical attention-based bidirectional LSTM model that considers both the sequence of words in each sentence and the sequence of sentences. Branting et al. (2017) consider administrative adjudication prediction in motion-rulings, Board of Veterans Appeals issue decisions, and World Intellectual Property Organization domain name dispute decisions. In this regard, three approaches for prediction are evaluated: maximum entropy over token n-grams, SVM over token n-grams, and a hierarchical attention network (Yang et al. 2016) applied to the full text. While no absolute winner was observed, the study highlights the benefit of using feature weights or network attention weights from these predictive models to identify salient phrases in motions or contentions and case facts. Nguyen et al. (2017, 2018) propose several approaches to train long short term memory (LSTMs) models and conditional random field (CRF) models for the problem of identifying two key portions of legal documents, i.e., requisite and effectuation segments, with evaluation on Japanese civil code and Japanese National Pension Law dataset. In Chalkidis and Kampas (2019) by Chalkidis and Kampas, a major contribution is the development of word2vec skip-gram embeddings trained on large legal corpora (mostly from European, UK, and US legislations).

Note that our work is clearly different from the aforementioned ones, since they not only focus on legal corpora other than Italian civil law articles but also they consider machine learning and neural network models that do not exploit the same ability as pre-trained deep language models.

To address the problem of predicting the final charges according to the fact descriptions in criminal cases, Hu et al. (2018) propose to exploit a set of categorical attributes to discriminate among charges (e.g., violence, death, profit purpose, buying and selling). By leveraging these annotations of charges based on representative attributes, the proposed learning framework aims to predict attributes and charges of a case simultaneously. An attribute attention mechanism is first applied to select factual information from facts that are relevant to each particular attribute, so to generate attribute-aware fact representations that can be used to predict the label of an attribute, under a binary classification task. Then, for the task of charge prediction, the attribute-aware fact representations aggregated by average pooling are also concatenated with the attribute-free fact representations produced by a conventional LSTM neural network. The training objective is twofold, as it minimizes the cross-entropy loss of charge prediction and the cross-entropy loss of attribute prediction.

It should be noticed that the above study was especially designed to deal with the typical imbalance of the case numbers of various charges as well as to distinguish related or "confusing" charges. In particular, the first aspect corresponds to a challenge of insufficient training data for some charges, as there are indeed charges with limited cases. This appears to be in analogy with the few-shot learning scenario in law article prediction; therefore, in Sect. 8.3, we shall present a comparative evaluation stage with the method in Hu et al. (2018) adapted for the ICC law article prediction task.

Also in the context of legal judgment prediction, Li et al. (2019) propose a multichannel attention-based neural network model, dubbed MANN, that exploits not only the case facts but also information on the defendant persona, such as traits that determine the criminal liability (e.g., age, health condition, mental status) and criminal records. A two-tier structure is used to empower attention-based sequence encoders to hierarchically model the semantic interactions from different parts of case description. Results on datasets of criminal cases in mainland China have shown improvements over other neural network models for judgment prediction, althugh MANN may suffer from the imbalanced classes of prison terms and cannot deal with criminal cases with multiple defendants. More recently, Gan et al. (2021) have proposed to inject legal knowledge into a neural network model to improve performance and interpretability of legal judgment prediction. The key idea is to model declarative legal knowledge as a set of first-order logic rules and integrate these logic rules into a co-attention network based model (i.e., bidirectional information flows between facts and claims) in an end-to-end way. The method has been evaluated on a collection of private loan law cases, where each instance in the dataset consists of a fact description and the plaintiff's multiple claims, demonstrating some advantage over AutoJudge (Long et al. 2019), which models the interactions between claims and fact descriptions via pair-wise attention in a judgment prediction task.

The above two works are distant from ours, not only in terms of the target corpora and addressed problems but also since we do not use any type of information other than the text of the articles, nor any injected knowledge base.

In the last few years, the Competition on Legal Information Extraction/ Entailment (COLIEE) has been an important venue for displaying studies focused on case/ statute law retrieval, entailment, and question answering. In most works appeared in the most recent COLIEE editions, the observed trend is to tackle the retrieval task by using CNNs and RNNs in the entailment phase, possibly in combination of additional features produced by applying classic term relevance weighting methods (e.g., TF-IDF, BM25) or statistical topic models (e.g., Latent Dirichlet Allocation). For instance, Kim et al. (2015) propose a binary CNN-based classifier model for answering to the legal queries in the entailment phase. The entailment model introduced by Morimoto et al. (2017) is instead based on MLP incorporating the attention mechanism. Nanda et al. (2017) adopt a combination of partial string matching and topic clustering for the retrieval task, while they combine LSTM and CNN models for the entailment phase. Do et al. (2017) propose a CNN binary model with additional TF-IDF and statistical latent semantic features.

The aforementioned studies differ from ours as they mostly focus on CNN and RNN based neural network models, which are indeed used as competing methods against our proposed deep-pretrained language model framework (cf. Sect. 8.3).

Exploiting BERT for law classification tasks has recently attracted much attention. Besides a study on Japanese legal term correction proposed by Yamakoshi et al. (2019), a few very recent works address sentence-pair classification problems in legal information retrieval and entailment scenarios. Rabelo et al. (2019) propose to combine similarity based features and BERT fine-tuned to the task of case law entailment on the data provided by the Competition on Legal Information Extraction/Entailment (COLIEE), where the input is an entailed fragment from a case coupled with a candidate entailing paragraph from a noticed case. Sanchez et al. (2020) employ BERT in its regression form to learn complex relevance criteria to support legal search over news articles. Specifically, the input consists of a query-document pair, and the output is a predicted relevance score. Results have shown that BERT trained either on a combined title and summary field of documents or on the documents' contents outperform a learning-to-rank approach based on LambdaMART equipped with features engineered upon three groups of relevance criteria, namely topical relevance, factual information, and language quality. However, in legal case retrieval, the query case is typically much longer and more complex than common keyword queries, and the definition of relevance between a query case and a supporting case could be beyond general topical relevance, which makes it difficult to build a large-scale case retrieval dataset. To address this challenge, Shao et al. (2020) propose a BERT framework to model semantic relationships to infer the relevance between two cases by aggregating paragraph-level dependencies. To this purpose, the BERT model is fine-tuned with a relatively small-scale case law entailment dataset to adapt it to the legal scenario. Experiments conducted on the benchmark of the relevant case retrieval task in COLIEE 2019 have shown effectiveness of the proposed BERT model.

We notice that the above two works require to classify query-document pairs (i.e., pairs of query and news article, in Sanchez et al. (2020), or pairs of case law documents, in Shao et al. (2020)), whereas our models are trained by using articles only. At the time of submission of this article, we also become aware of a small bunch of works presented at COLIEE-2020 that compete for the statute law retrieval and question answering (statute entailment) tasks[1] using BERT (Rabelo et al. 2020). In particular, for the statute law retrieval task, the goal is to read a legal bar exam question and retrieve a subset of Japanese civil code articles to judge whether the question is entailed or not. The BERT-based approach has shown to improve overall retrieval performance, although there are still numbers of questions that are difficult to retrieve by BERT too. At COLIEE-2021, which was held in June 2021,[2] there has been an increased attention and development of BERT-based methods to address the statute and case law processing tasks (Yoshioka et al. 2021; Nguyen et al. 2021).

Again, it should be noted that the above works at COLIEE Competitions assume that the training data are questions and relevant article pairs, whereas our training data instances are derived from articles only. Nonetheless, we recognize that some of the techniques introduced at COLIEE-2021, such as deploying weighted aggregation on models' predictions and the iterated self-labeled and fine-tuning process, are worthy of investigation and we shall delve into them in our future research.

In addition to the COLIEE Competitions, it is worth mentioning the study by Chalkidis et al. (2019a), which provides a threefold contribution. They release a new

[1] https://sites.ualberta.ca/~rabelo/COLIEE2020/.

[2] https://sites.ualberta.ca/~rabelo/COLIEE2021/.

dataset of cases from the European Court of Human Rights (ECHR) for legal judgment prediction, which is larger (about 11.5k cases) than earlier datasets, and such that each case along with its list of facts is mapped to articles violated (if any) and is assigned an ECHR importance score. The dataset is used to evaluate a selection of neural network models, for different tasks, namely binary classification (i.e., whether a case violates a human rights article or not), multi-label classification (i.e., which types of violation, if any), and case importance detection. Results have shown that the neural network models outperform an SVM model with bag-of-words features, which was previously used in related work such as (Aletras et al. 2016). Moreover, a hierarchical version of BERT, dubbed HIER-BERT, is proposed to overcome the BERT's maximum length limitation, by first generating fact embeddings and then using them through a self-attention mechanism to produce case embeddings, similarly to a hierarchical attention network model (Yang et al. 2016).

The latter aspect on the use of a hierarchical attention mechanism, especially when integrated into BERT, is very interesting and useful on long legal documents, such as case law documents, to improve the performance of pre-trained language models like BERT that are designed with constraints on the tokenized text length. Nonetheless, as we shall discuss later in Sect. 4.4, this contingency does not represent an issue in the setting of our proposed framework, due not only to the characteristic length of ICC articles but also to our designed schemes of unsupervised training-instance labeling.

3 Data

The Italian Civil Code (ICC) is divided into six, logically coherent books, each in charge of providing rules for a particular civil law theme:

- *Book-1*, on Persons and the Family, articles 1-455–contains the discipline of the juridical capacity of persons, of the rights of the personality, of collective organizations, of the family;
- *Book-2*, on Successions, articles 456-809—contains the discipline of succession due to death and the donation contract;
- *Book-3*, on Property, articles 810-1172—contains the discipline of ownership and other real rights;
- *Book-4*, on Obligations, articles 1173-2059—contains the discipline of obligations and their sources, that is mainly of contracts and illicit facts (the so-called civil liability);
- *Book-5*, on Labor, articles 2060-2642—contains the discipline of the company in general, of subordinate and self-employed work, of profit-making companies and of competition;
- *Book-6*, on the Protection of Rights, articles 2643-2969—contains the discipline of the transcription, of the proofs, of the debtor's financial liability and of the causes of pre-emption, of the prescription.

Table 1 Main statistics on the ICC corpus and its constituent books

ICC	#Arts.	#Sentences over the articles				#Words over the articles			
portion		*tot.*	*min*	*max*	*mean* (*std*)	*tot.*	*min*	*max*	*mean* (*std*)
Book-1	395	1979	3	21	5.010 (2.323)	32,354	11	569	81.909 (71.952)
Book-2	345	1561	3	13	4.525 (1.675)	24,520	9	354	71.072 (51.366)
Book-3	364	1619	3	24	4.448 (1.816)	25,971	6	893	71.349 (65.836)
Book-4	891	3595	3	12	4.035 (1.338)	50,509	7	365	56.688 (38.837)
Book-5	713	3937	3	37	5.522 (3.191)	75,764	8	1465	106.261 (117.393)
Book-6	331	1453	3	17	4.390 (1.895)	25,937	12	654	78.360 (76.954)
All	3039	14,131	3	37	4.650 (2.243)	234,945	6	1465	77.310 (78.373)

The articles of each book are internally organized into a hierarchical structure based on four levels of division, namely (from top to bottom in the hierarchy): “titoli” (i.e., chapters), “capi” (i.e., subchapters), “sezioni” (i.e., sections), and “paragrafi” (i.e., paragraphs). It should however be emphasized that this hierarchical classification was not meant as a crisp, ground-truth organization of the articles’ contents: indeed, the topical boundaries of contiguous chapters and subchapters are often quite smooth, as articles in the same group often not only vary in length but can also provide dispositions that are more related to articles in other groups.

The ICC is obviously publicly available, in various digital formats. From one of such sources, we extracted *article id*, *title* and *content* of each article. We cleaned up the text from non-ASCII characters, removed numbers and date, normalized all variants and abbreviations of frequent keywords such as “articolo” (i.e., article), “decreto legislativo” (i.e., legislative decree), “Gazzetta Ufficiale” (i.e., Official Gazette), and finally we lowercased all letters.

The ICC currently in force was enacted by Royal decree no. 262 of 16 March 1942, and it consists of 2969 articles. This number actually corresponds to 3225 articles considering all variants and subsequent insertions, which are designated by using Latin-term suffixes (e.g., “bis”, “ter”, “quater”). However, during its history, the ICC was revised several times and subjected to repealings, i.e., per-article partial or total insertions, modifications and removals; to date, 2294 articles have been repealed. Table 1 summarizes main statistics on the preprocessed ICC books.

4 The proposed LamBERTa framework

In this section we present our proposed learning framework for civil-law article retrieval. We first formulate the problem statement in Sect. 4.1 and overview the framework in Sect. 4.2. We present our devised learning approaches in Sect. 4.3. We describe the data preparation and preprocessing in Sect. 4.4, then in Sect. 4.5

we define our unsupervised training-instance labeling methods for the articles in the target corpus. Finally, in Sect. 4.6, we discuss major settings of the proposed framework.

4.1 Problem setting

Our study is concerned with law article retrieval, i.e., finding articles of interest out of a legal corpus that can be recommended as an appropriate response to a query expressing a legal matter.

To formalize this problem, we assume that any query is expressed in natural language and discusses a legal subject that is in principle covered by the target legal corpus (i.e., the ICC, in our context). Moreover, a query is assumed to be free of references to any article identifier in the ICC.

We address the law article retrieval task based on the supervised machine learning paradigm: given a new, user-provided instance, i.e., a legal question, the goal is to automatically predict the category associated to the posed question. More precisely, we deal with the more general case in which a probability distribution over all the predefined categories is computed in response to a query. The prediction is carried out by a machine learning system that is trained on a target legal corpus—whose documents, i.e., articles, are annotated with the actual category they belong to—in order to learn a computational model, also called classifier, that will then be used to perform the predictions against legal queries by exclusively utilizing the textual information contained in the annotated documents.

4.1.1 Motivations for BERT-based approach

In this respect, our objective is to leverage deep neural-network-based, pre-trained language modeling to solve the law article retrieval task. This has a number of key advantages that are summarized as follows. First, like any other deep neural network models, it totally avoids manual feature engineering, and hence the need for employing feature selection methods as well as feature relevance measures (e.g., TF-IDF). Second, like sophisticated recurrent and convolutional neural networks, it models language semantics and non-linear relationships between terms; however, better than recurrent and convolutional neural networks and their combinations, it is able to capture subtle and complex lexical patterns including the sequential structure and long-term dependencies, thus obtaining the most comprehensive local and global feature representations of a text sequence. Third, it incorporates the so-called *attention* mechanism, which allows a learning model to assign higher weight to text features according to their higher informativeness or relevance to the learning task. Fourth, being a real bidirectional *Transformer* model, it overcomes the main limitations of early deep contextualized models like ELMO (Peters et al. 2018) (whose left-to-right language model and right-to-left language model are actually independently trained) or decoder-based Transformer models, like OpenAI GPT (Radford and Sutskever 2018).

4.1.2 Challenges

It should however be noted that, like any other machine learning method, using deep pre-trained models like BERT for classification tasks normally requires the availability of data annotated with the class labels, so to design the independent training and testing phases for the classifier. However, this does not apply to our context.

As previously mentioned, in this work we face three main challenges:

- the first challenge refers to the high number (i.e., hundreds) of classes, which correspond to the number of articles in the ICC corpus, or portion of it, that is used to train a LamBERTa model;
- the second challenge corresponds to the so-called *few-shot learning* problem, i.e., dealing with a small amount of per-class examples to train a machine learning model, which Bengio et al. recognize as one of the “extreme classification” scenarios (Bengio et al. 2019).
- the third challenge derives from the unavailability of test query benchmarks for Italian legal article retrieval/prediction tasks. This has prompted us to define appropriate methods for data annotation, thus for building up training sets for the LamBERTa framework. To address this problem, we originally define different schemes of *unsupervised training-instance labeling*; notably, these are not ad-hoc defined for the ICC corpus, rather they can be adapted to any other law code corpus.

In the following, we overview our proposed deep pre-trained model based framework that is designed to address all the above challenges.

4.2 Overview of the LamBERTa framework

Figure 1 shows the conceptual architecture of our proposed LamBERTa – **L**aw **a**rticle **m**ining based on **BERT** **a**rchitecture. The starting point is a pre-trained Italian BERT model whose source data consists of a recent Wikipedia dump, various texts from the OPUS corpora collection, and the Italian part of the OSCAR corpus; the final training corpus has a size of 81GB and 13 138 379 147 tokens.[3]

LamBERTa models are generated by fine-tuning the pre-trained Italian BERT model on a sequence classification task (i.e., BERT with a single linear classification layer on top) given in input the articles of the ICC or a portion of it.

[3] bert-base-italian-xxl-uncased, available at https://huggingface.co/dbmdz/.

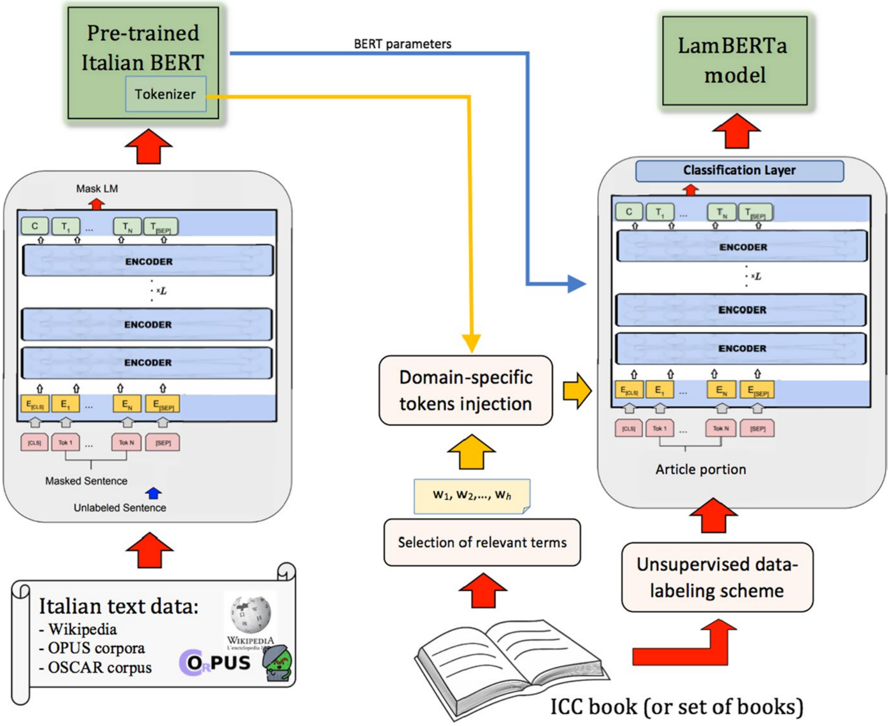


Fig. 1 An illustration of the conceptual architecture of LamBERTa designed for the ICC law article retrieval task

It is worth noting that the LamBERTa architecture is versatile w.r.t. the adopted learning approach and the training-instance labeling scheme for a given corpus of ICC articles. These aspects are elaborated on next.

4.3 Global and local learning approaches

We consider two learning approaches, here dubbed *global* and *local* learning, respectively. A **global model** is trained on the whole ICC, whereas a **local model** is trained on a particular book of the ICC.[4] Our rationale underlying this choice is as follows:

- on the one hand, local models are designed to embed the logical coherence of the articles within a particular book and, although limited to its corresponding topi-

[4] From a technical viewpoint, the considered portion could in principle include any strict subset of the ICC; however, on the legal domain side, it is reasonable to learn local models each dedicated to a logically coherent subset of the whole civil code, i.e., a single book.

Table 2 Number of domain-specific tokens to inject into the pre-trained BERT vocabulary and the final vocabulary size

ICC Portion	#Added Tokens	Vocab. Size
Book-1	833	31,935
Book-2	698	31,800
Book-3	1072	32,174
Book-4	1383	32,485
Book-5	2048	33,150
Book-6	829	31,931
All	3993	35,095

cal boundaries, they are expected to leverage the multi-faceted semantics underlying a specific civil law theme (e.g., inheritage);

- on the other hand, books are themselves part of the same law code, and hence a global model might be useful to capture possible interrelations between the single books, however, by embedding different topic signals from different books (e.g. inheritage of Book-2 vs. labor law of Book-5), it could incur the risk of topical dilution over all the ICC.

Either type of model is designed to be a *classifier at article level*, i.e., class labels correspond to the articles in the book(s) covered by the model. Given the one-to-one association between classes and articles, a question becomes how to create suitable training sets for our LamBERTa models. Our key idea is to adopt an *unsupervised annotation* approach, which is discussed in the next section.

4.4 Data preparation

To tailor the ICC articles to the BERT input format, we initially carried out segmentation of the content of each article into sentences. This was then followed by tokenization of the sentences and text encoding, which are described next.

4.4.1 Domain-specific terms injection and tokenization

BERT was trained using the WordPiece tokenization. This is an effective way to alleviate the open vocabulary problems in neural machine translation, since a word can be broken down into sub-word units, which are constructed during the training time and depend on the corpus the model was initially trained on.

However, when retraining BERT on the ICC articles to learn global as well as local models, it is likely that some important terms occurring in the legal texts are missing in the pre-trained lexicon; therefore, to make BERT aware of the domain-specific (i.e., legal) terms and avoid subwording such terms thus disrupting their semantics, we injected a selection of terms from the ICC articles into the pre-existing BERT vocabulary before tokenization.[5]

To select the domain-specific terms to be added, we carried out the following steps: if we denote with *D* the input (portion of) ICC text for the model to learn, we first preprocessed the text *D* as described in Sect. 3, then we removed Italian stopwords, and finally filtered out overly frequent terms (as occurring in more than 50% of the articles in *D*) as well as hapax terms. Table 2 reports the number of added tokens and the final number of tokens, for each input corpus to our LamBERTa local and global models.

4.4.2 Text encoding

BERT utilizes a fixed sequence size (usually 512) for each tokenized text, which implies both padding of shorter sequences and truncation of longer sequences. While padding has no side effect, truncation may produce loss of information.

In learning our models, we wanted to avoid the above aspect, therefore we investigated any condition causing such undesired effect in our input data. We found out that this contingency is very rare in each book of the ICC, even reducing the maximum length to 256 tokens; the only situation that would lead to truncation corresponds to an article sentence that is logically organized in multiple clauses separated by semicolon: for these cases, we treated each of the subsentences as one training unit associated with the same article class-label.

4.5 Methods for unsupervised training-instance labeling

As previously discussed, our LamBERTa classification models are trained in such a way that it holds an one-to-one correspondence between articles in a target corpus and class labels. Moreover, the entire corpus must be used to train the model so to embed the whole knowledge therein. However, given the uniqueness of each article, the general problem we face is *how to create as many training instances as possible for each article* to effectively train the models.

Our key idea is to select and combine portions of each article to generate the training units for it. To this aim, we devise different unsupervised schemes for data labeling the ICC articles to create the training sets of LamBERTa models. Our schemes adopt different strategies for selecting and combining portions of each article to derive the training sets, but they share the requirements of generating a minimum number of training units per article, here denoted as *minTU*; moreover, since each article is usually comprised of few sentences, and *minTU* needs to be relatively large (we chose 32 as default value), each of the schemes implements a *round-robin* (RR) method that iterates over replicas of the same group of training units per article until at least *minTU* are generated.

[5] From the perspective of the BERT architecture, this implies two actions, namely indexing the added terms and initializing their corresponding weights.

In the following, we define our methods for unsupervised training-instance labeling of the ICC articles (in square brackets, we indicate the notation that will be used throughout the remainder of the paper):

- *Title-only* [T]. This is the simplest yet lossy scheme, which keeps an article's title while discarding its content; the round-robin block is just the title of an article.[6]
- *n-gram*. Each training unit corresponds to n consecutive sentences of an article; the round-robin block starts with the n-gram containing the title and ends with the n-gram containing the last sentence of the article. We set $n \in \{1, 2, 3\}$, i.e., we consider a unigram [UniRR], a bigram [BiRR], and a trigram [TriRR] model, respectively.
- *Cascade* [CasRR]. The article's sentences are cumulatively selected to form the training units; the round-robin block starts with the first sentence (i.e., the title), then the first two sentences, and so on until all article's sentences are considered to form a single training unit.
- *Triangle* [TglRR]. Each training unit is either an unigram, a bigram or a trigram, i.e., the round-robin block contains all n-grams, with $n \in \{1, 2, 3\}$, that can be extracted from the article's title and description.
- *Unigram with parameterized emphasis on the title* [UniRR.T$^+$]. The set of training units is comprised of one subset containing the article's sentences with round-robin selection, and another subset containing only replicas of the article's title. More specifically, the two subsets are formed as follows:
    - The first subset is of size equal to the maximum between the number of article's sentences and the quantity $m \times mean\_s$, where m is a multiplier (set to 4 as default) and $mean\_s$ expresses the average number of sentences per article, excluding the title. As reported in Table 1 (sixth column), this mean value can be recognized between 3 and 4—recall that the title is excluded from the count— therefore we set $mean\_s \in \{3, 4\}$.
    - The second subset finally contains $minTU - m \times mean\_s$ replicas of the title.
- *Cascade with parameterized emphasis on the title* [CasRR.T$^+$] and *Triangle with parameterized emphasis on the title* [TglRR.T$^+$]. These two schemes follow the same approach as UniRR.T$^+$ except for the composition of the round-robin block, which corresponds to CasRR and TglRR, respectively, with the title left out from this block and replicated in the second block, for each article.

4.6 Learning configuration

An input to LamBERTa is of the form [CLS, ⟨*text*⟩, SEP], where CLS (stands for 'classification') and SEP are special tokens respectively at the beginning of each sequence and at separation of two parts of the input. These two special tokens are

[6] We point out that considering also the title of the group to which an article belongs (e.g., chapter, subchapter) would not add further information, since each article's title recalls yet specializes its group's title.

associated with two vectorial dense representations or *embeddings*, denoted as $E_{[CLS]}$ and $E_{[SEP]}$, respectively; analogously, there are as many embeddings E_i as the number of tokens of the input text. Note also that as discussed in Sect. 4.4, each sequence in a mini-batch is padded to the maximum length (e.g., 256 tokens) in the batch. In correspondence of each input embedding E_i, an embedding T_i is outputted, and it can be seen as the contextual representation of the *i*-th token of the input text. Instead, the final hidden state, i.e., output embedding C, corresponding to the CLS token captures the high level representation of the entire text to be used as input to further levels in order to train any sentence-based task, such as sentence classification. This vector, which is by design of size 768, is fed to a single layer neural network followed by sigmoid activation whose output represents the distribution probability over the law articles of a book.

LamBERTa models were trained using a typical configuration of BERT for masked language modeling, with 12 attention heads and 12 hidden layers, and initial (i.e., pre-trained) vocabulary of 32 102 tokens. Each model was trained for 10 epochs, using cross-entropy as loss function, Adam optimizer and initial learning rate selected within [1e-5, 5e-5] on batches of 256 examples.

It should be noted that our LamBERTa models can be seen as relatively light in terms of computational requirements, since we developed them under the Google Colab GPU-based environment with a limited memory of 12 GB and 12-hour limit for continuous assignment of the virtual machine.[7]

5 Explainability of LamBERTa models based on Attention Patterns

In this section, we start our understanding of what is going on inside the “black box” of LamBERTa models. One important aspect is the *explainability* of LamBERTa models, which we investigate here focusing on the formation of complex relationships between tokens.

Like any BERT-based architecture, our LamBERTa leverages the Transformer paradigm, which allows for processing all elements simultaneously by forming direct connections between individual elements through a mechanism known as *attention*. Attention is a way for a model to assign weight to input features (i.e., parts of the texts) based on their high informativeness or importance to some task. In particular, attention enables the model to understand how the words relate to each other in the context of the sentence, by forming composite representations that the model can reason about.

BERT’s attention patterns can assume several forms, such as delimiter-focused, bag-of-words, and next-word patterns. Through the lens of the `bertviz` visualization tool,[8] we show how LamBERTa forms its distinctive attention patterns. For this purpose, here we present a selection of examples built upon sentences from Book-2

[7] https://colab.research.google.com/.

[8] https://github.com/jessevig/bertviz.

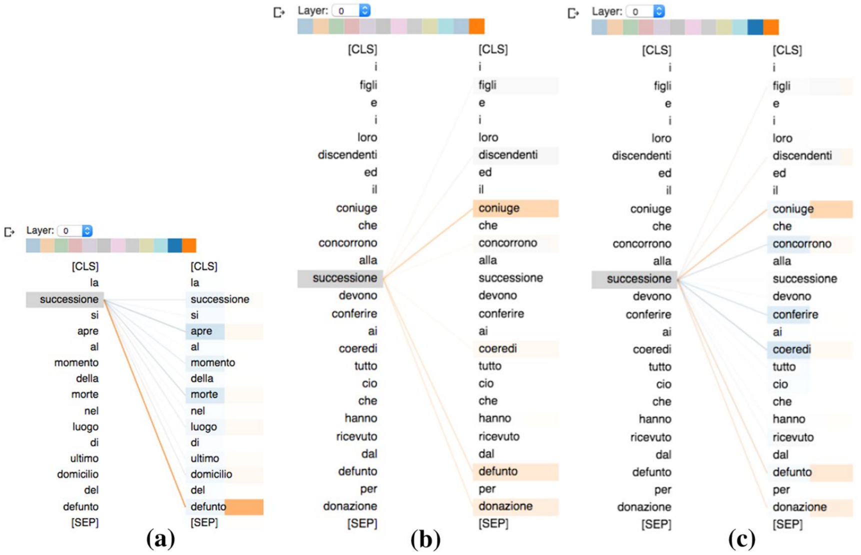

Layer: 0
[CLS] la successione si apre al momento della morte nel luogo di ultimo domicilio del defunto [SEP]
(a)
Layer: 0
[CLS] i figli e i loro discendenti ed il coniuge che concorrono alla successione devono conferire ai coeredi tutto cio che hanno ricevuto dal defunto per donazione [SEP]
(b)
Layer: 0
[CLS] i figli e i loro discendenti ed il coniuge che concorrono alla successione devono conferire ai coeredi tutto cio che hanno ricevuto dal defunto per donazione [SEP]
(c)

Fig. 2 Attention patterns for "succession": **a** two-head pattern from Art. 456 and comparison with **b** single-head and **c** two-head patterns from Art. 737

of the ICC (i.e., relevant to key concepts in inheritance law), which are next reported both in Italian and English-translated versions.

The attention-head view in `bertviz` visualizes attention patterns as lines connecting the word being updated (left) with the word(s) being attended to (right), for any given input sequence, where color intensity reflects the attention weight. Figure 2a–c shows noteworthy examples focused on the word "succession", from the following sentences:

> from Art. 456: *"la successione si apre al momento della morte nel luogo dell'ultimo domicilio del defunto"* (i.e., "the succession opens at the moment of death in the place of the last domicile of the deceased person")
> from Art. 737: *"i figli e i loro discendenti ed il coniuge che concorrono alla successione devono conferire ai coeredi tutto ciò che hanno ricevuto dal defunto per donazione"* (i.e., the children and their descendants and the spouse who contribute to the succession must give to the co-heirs everything they have received from the deceased person as a donation)

In Fig. 2a, we observe how the source is connected to a meaningful, non-contiguous set of words, particularly, "apre" ("opens"), "morte" ("death"), and "defunto" ("deceased person"). In addition, in Fig. 2b, we observe how "successione" is related to "coniuge" ("spouse"), "donazione" ("donation"), which is further enriched in the two-head attention patterns with "coeredi" ("co-heirs"), "conferire" ("give"), and "concorrono" ("contribute"), shown in Fig. 2c; moreover, "successione" is still connected to "defunto". Remarkably, these patterns highlight the model's ability not only to mine semantically meaningful patterns that are more complex than next-word or delimiter-focused patterns, but also to build patterns that consistently hold across various sentences sharing words. Note that, as shown in our examples, these sentences can belong to different contexts (i.e., different articles), and can significantly vary in length. The latter point is particularly evident, for instance, in the following example sentences:

> from Art. 457: *"l'eredità si devolve per legge o per testamento. Non si fa luogo alla successione legittima se non quando manca, in tutto o in parte, quella testamentaria"* (i.e., "the inheritance is devolved by law or by will. There is no place for legitimate succession except when the testamentary succession is missing, in whole or in part")
> from Art. 683: *"la revocazione fatta con un testamento posteriore conserva la sua efficacia anche quando questo rimane senza effetto perché l'erede istituito o il legatario è premorto al testatore, o è incapace o indegno, ovvero ha rinunziato all'eredità o al legato"* (i.e., " the revocation made with a later will retains its effectiveness even when this remains without effect because the established heir or legatee is premortal to the testator, or is incapable or unworthy, or has renounced the inheritance or the legacy")

Focusing now on "eredità" ("inheritance"), in Art. 457 we found attention patterns with "testamento" ("testament"), "legittima" ("legitimate"), "testamentaria" ("testamentary succession"), whereas in the long sentence from Art. 683, we again found a link to "testamento" ("testament") as well as with the related concept "testatore" ("testator"), in addition to connections with "premorto" ("premortal"), "indegno" ("unworthy"), and "rinunziato" ("renounced").

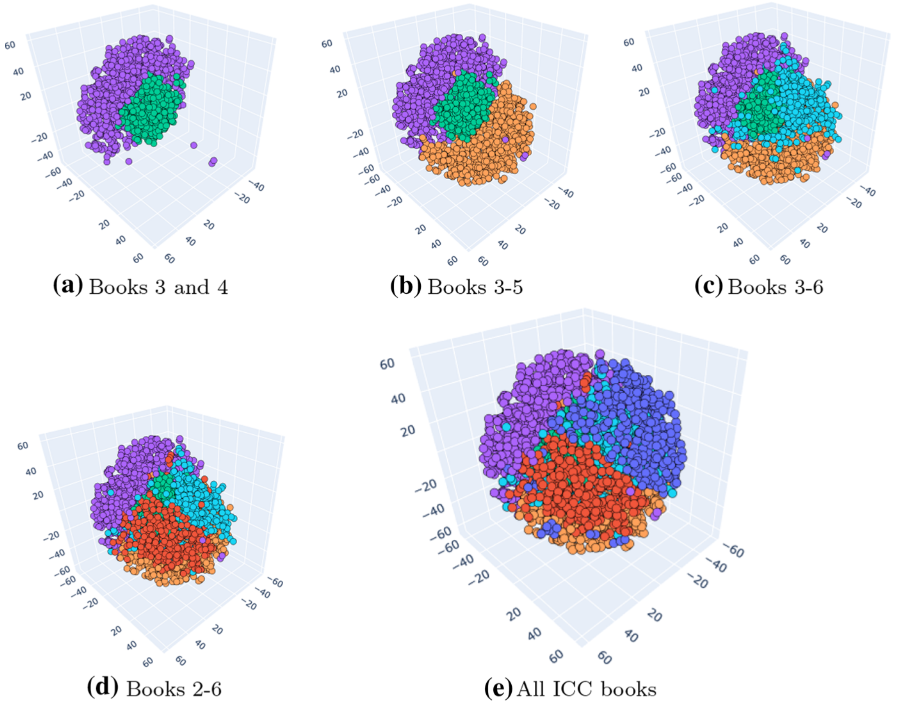
We point out that our investigation of LamBERTa models' attention patterns was found to be persistent over different input sequences, besides the above discussed examples. This has unveiled the ability of LamBERTa models to form different types of patterns, which include complex bag-of-words and next-word patterns.

6 Visualization of ICC LamBERTa Embeddings

Our qualitative evaluation of LamBERTa models is also concerned with the core outcome of the models, that is, the learned representation embeddings for the inputted text.

As previously mentioned in Sect. 4.6, for any given text in input, a real-valued vector C of length 768 is produced downstream of the 12 layers of a BERT model, in correspondence with the input embedding $E_{[CLS]}$ relating to the special token CLS. This output embedding C can be seen as an encoded representation of the input text supplied to the model.

In the following, we present a visual exploratory analysis of LamBERTa embeddings based on a powerful, widely-recognized method for the visualization of high-dimensional data, namely *t-Distributed Stochastic Neighbor Embedding* (t-SNE) (van der Maaten and Hinton 2008). t-SNE is a non-linear technique for dimensionality reduction that is highly effective at providing an intuition of how the data is arranged in a high-dimensional space. The t-SNE algorithm calculates a similarity



(a) Books 3 and 4

(b) Books 3-5

(c) Books 3-6

(d) Books 2-6

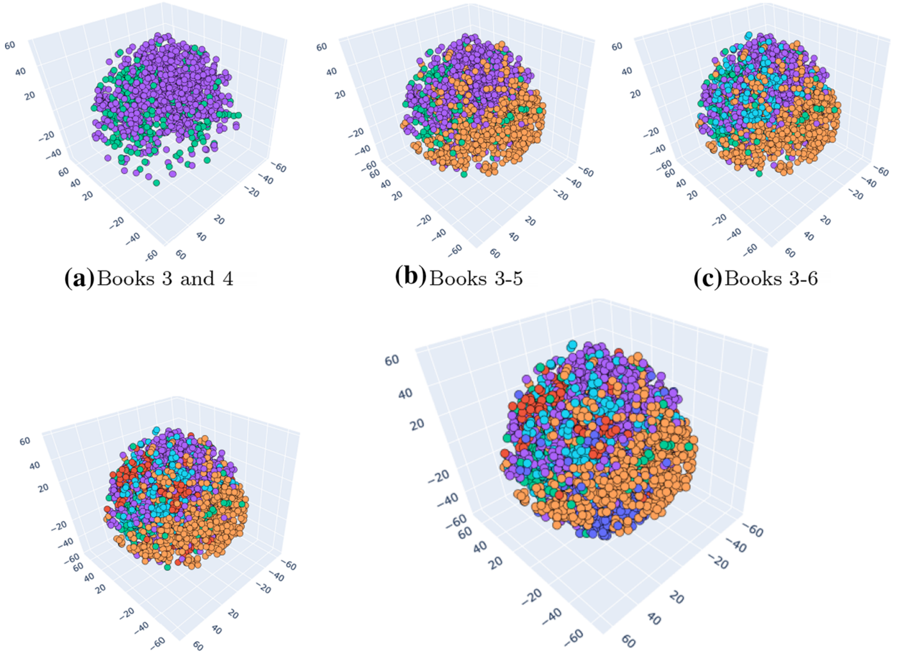
(e) All ICC books

Fig. 3 Visualization of the ICC article embeddings produced by LamBERTa local models, transformed onto a 3D t-SNE space. Color codes correspond to ICC books: blue for Book-1, red for Book-2, green for Book-3, purple for Book-4, orange for Book-5, cyan for Book-6

measure between pairs of instances in the high-dimensional space and in the low-dimensional space, usually 2D or 3D. Then, it converts the pairwise similarities to joint probabilities and tries to minimize the Kullback-Leibler divergence between the joint probabilities of the low-dimensional embedding and the high-dimensional data.

It is well-known that t-SNE outputs provide better and more interpretable results than Principal Component Analysis (PCA) and other linear dimensionality reduction models, which are not effective at interpreting complex polynomial relationships between features. In particular, by seeking to maximize variance and preserving large pairwise distances, the classic PCA focuses on placing dissimilar data points far apart in a lower dimension representation; however, in order to represent high-dimensional data on low-dimensional, non-linear manifold, it is important that similar data points must be represented close together. This is ensured by t-SNE, which preserves small pairwise distances or local similarities (i.e., nearest-neighbors), so that similar points on the manifold are mapped to similar points in the low-dimensional representation.

Figure 3 displays 3D t-SNE representations of the article embeddings generated by LamBERTa local models, for each book of the ICC. (Each point represents the



(a) Books 3 and 4 **(b)** Books 3-5 **(c)** Books 3-6

(d) Books 2-6 **(e)** All ICC books

Fig. 4 Visualization of the ICC article embeddings produced by LamBERTa global model, transformed onto a 3D t-SNE space. Color coding is the same as in Fig. 3

t-SNE transformation of the embedding of an article onto a 3D space, while colors are used to distinguish the various books.) In the figure, we show progressive combinations of the results from different books,[9] while the last chart corresponds to the whole ICC. This choice of presentation is motivated to ease the readability of each book's article embeddings. It can be noted that the LamBERTa local models are able to generate embeddings so that t-SNE can effectively put nearest-neighbor cases together, with a certain tendency of distributing the points from different books in differest subspaces.

Let us now compare the above results with those from Fig. 4, which shows the 3D t-SNE representations of the article embeddings generated by LamBERTa global model.[10] From the comparison, we observe a less compact and localized representation in the global model embeddings w.r.t. the local model ones. This is interesting yet expected, since global models are designed to go beyond the boundaries of a

[9] The order of combination of the books is just due to the sake of presentation.

[10] In both local and global settings, t-SNE was carried out until convergence, with the default value of *perplexity*, which is a key parameter to control the number of effective nearest neighbors in the manifold learning. Notably, we tried different values for the perplexity, both within and outside the recommended range (i.e., 5-50), but the difference in the visual analysis results between the global and local cases still remained the same.

book, whereas local models focus on the interrelations between articles on the same book.

It should be noted that while the above remark would hint at preferring the use of local models against global models, at least in terms of interpretability based on visual exploratory analysis, we shall deep our understanding on the effectiveness of the two learning approaches in the next section, which is dedicated to the presentation and discussion of our extensive, quantitative experimental evaluation of LamBERTa models.

7 Experimental evaluation

In this section we present the methodology and results of an experimental evaluation that we have thoroughly carried out on LamBERTa models. In the following, we first state our evaluation goals in Sect. 7.1, then we define the types of test queries and select the datasets in Sect. 7.2, finally we describe our methodology and assessment criteria in Sect. 7.3.

7.1 Evaluation goals

Our main evaluation goals can be summarized as follows:

- To validate and measure the effectiveness of LamBERTa models for law article retrieval tasks: how do local and global models perform on different evaluation contexts, i.e., against queries of different type, different length, and different lexicon? (Sect. 8.1)
- To evaluate LamBERTa models in single-label as well as multi-label classification tasks: how do they perform w.r.t. different assumptions on the article relevance to a query, particularly depending on whether a query is originally associated with or derived from a particular article, or by-definition associated with a group of articles? (Sect. 8.1)
- To understand how a LamBERTa model's behavior is affected by varying and changing its constituents in terms of training-instance labeling schemes and learning parameters (Sect. 8.2).
- To demonstrate the superiority of our classification-based approach to law article retrieval by comparing LamBERTa to other deep-learning-based text classifiers (Sect. 8.3.1) and to a few-shot learner conceived for an attribute-aware prediction task that we have newly designed based on the ICC heading metadata (Sect. 8.3.2).

7.2 Query sets

A query set is here meant as a collection of natural language texts that discuss legal subjects relating to the ICC articles. For evaluation purposes, each query as a test instance is associated with one or more article-class labels.

It should be emphasized that, on the one hand, we cannot devise a training-test split or cross-validation of the target ICC corpus (since we want that our LamBERTa models embed the knowledge from all articles therein), and on the other hand, there is a lack of query evaluation benchmarks for Italian civil law documents. Therefore, we devise different types of query sets, which are aimed at representing testbeds at varying difficulty level for evaluating our LamBERTa models:

- QType-1—*book-sentence-queries* refer to a set of queries that correspond to randomly selected sentences from the articles of a book. Each query is derived from a single article, and multiple queries are from the same article.
- QType-2—*paraphrased-sentence-queries* share the same composition of QType-1 queries but differ from them as the sentences of a book's articles are paraphrased. To this purpose, we adopt a simple approach based on backtranslation from English (i.e., an original sentence in Italian is first translated to English, then the obtained English sentence is translated to Italian).[11]
- QType-3—*comment-queries* are defined to leverage the publicly available *comments* on the ICC articles provided by legal experts through the platform "Law for Everyone".[12] Such comments are delivered to provide annotations about the interpretation of the meanings and law implications associated to an article, or to particular terms occurring in an article. Each query corresponds to a comment available about one article, which is a paragraph comprised of about 5 sentences on average.
- QType-4—*comment-sentence-queries* refer to the same source as QType-3, but the comments are split into sentences, so that each query contains a single sentence of a comment. Therefore, each query will be associated to a single article, and multiple queries will refer to the same article.
- QType-5—*case-queries* refer to a collection of case law decisions from the civil section of the Italian Court of Cassation, which is the highest court in the Italian judicial system. These case law decisions are selected from publicly available corpora of the most significant jurisprudential sentences associated with the ICC articles, spanning over the period 1977-2015.
- QType-6—*ICC-heading-queries* are defined by extracting the headings of chapters, subchapters, and sections of each ICC book. Such headings are very short, ranging from one to few keywords used to describe the topic of a particular division of a book.

[11] We used the Google Translate service, which is a widely-used yet effective machine translator.

[12] *Law for Everyone* online news portal, available at https://www.laleggepertutti.it.

Table 3 Main statistics on the test query sets

ICC portion	Query type	#Queries	#Words	Query Type	#Queries	#Words	#Sentences
Book-1	QType-1	790	13,436	QType-3	331	38,383	1262
Book-2	QType-2	690	10,998	QType-4	322	30,226	1000
Book-3		728	11,942		286	23,815	781
Book-4		1774	27,352		764	85,360	2640
Book-5		1426	22,754		570	87,094	2417
Book-6		662	11,993		294	31,898	1040

ICC portion	Query type	#Queries	#Words	Year range
Book-1	QType-5	333	39,464	1978–2014
Book-2		347	36,856	1979–2014
Book-3		371	39,643	1979–2014
Book-4		975	111,234	1978–2015
Book-5		1037	114,287	1977–2015
Book-6		720	81,186	1978–2015

ICC portion	Query type	#Chapter queries	#Subchapter queries	#Section queries	#Total words
Book-1	QType-6	14	25	22	317
Book-2		5	30	14	160
Book-3		9	21	29	230
Book-4		9	51	57	366
Book-5		11	11	51	397
Book-6		5	18	38	251

7.2.1 Characteristics and differences of the query-sets

It should be noted that while QType-1 and QType-6 query sets have the same lexicon as the corresponding book articles, this does not necessarily hold for QType-2 due to the paraphrasing process, and the difference becomes more evident with QType-3, QType-4, and QType-5 query sets. Indeed, the latter not only originate from a corpus different from the ICC, but they have the typical verbosity of annotations or comments about law articles as well as of case law decisions; moreover, they often provide cross-book references, therefore, QType-3, QType-4, and QType-5 query-set contents are not necessarily bounded by a book's context.

Moreover, QType-3, QType-5, and QType-6 differ from the other types in terms of length of each query, which corresponds indeed to multiple sentences or a paragraph, in the case of QType-3 and QType-5, and to a single or few keywords, in the case of QType-6. Note that, although derived from the ICC books, *the contents of the QType-6 queries were totally discarded when training our LamBERTa models*; moreover, unlike the other types of queries, each QType-6 query is by definition associated with a group of articles (i.e., according to the book divisions) rather than a single article, therefore we shall use QType-6 queries for the multi-label evaluation task only. Also, it should be emphasized that the QType-5 queries represent a different difficult testbed as they contain real-life, heterogeneous fact descriptions of the case and judicial precedents.

Table 3 summarizes main statistics on the query sets. In addition, note that the percentage of QType-1 that were paraphrased (i.e., to produce QType-2 queries) resulted in above 85% for each of the books. Also, the number of sentences in a book's query set (last column of the upper subtable) corresponds to the number of queries of QType-4 for that book.

It is also worth emphasizing that all query sets were validated by legal experts. This is important to ensure not only generic linguistic requirements but also meaningfulness of the query contents from a legal viewpoint.

7.3 Evaluation methodology and assessment criteria

Let us denote with $\mathcal{C}$ either a portion (i.e., a single book) of the ICC, or the whole ICC. We specify an evaluation context in terms of a test set (i.e., query set) Q pertinent to $\mathcal{C}$ and a LamBERTa model $\mathcal{M}$ learnt from $\mathcal{C}$. Note that the pertinence of Q w.r.t. $\mathcal{C}$ is differently determined depending on the type of query set, as previously discussed in Sect. 7.2.

We consider two multi-class evaluation contexts: *single-label* and *multi-label*. In the single-label context, each query is pertinent to only one article, therefore there is only one relevant result for each query. In the multi-label context, each query can be pertinent to more than one article, therefore there can be multiple relevant results for each query.

7.3.1 Single-label evaluation context

We consider a confusion matrix in which the article ids correspond to the classes. Upon this matrix, we measure the following standard statistics for each article $A_i \in \mathcal{C}$: the precision for A_i (P_i), i.e., the number of times (queries) A_i was correctly predicted out of all predictions of A_i, the recall for A_i (R_i), i.e., the number of times (queries) A_i was correctly predicted out of all queries actually pertinent to A_i, the F-measure for A_i (F_i), i.e., $F_i = 2P_iR_i/(P_i + R_i)$. Then, we averaged over all articles to obtain the per-article average *precision* (P), *recall* (R), and two types of F-measure: *micro-averaged F-measure* (F^{μ}) as the actual average over all F_is, and *macro-averaged F-measure* (F^M) as the harmonic mean of P and R, i.e., $F^M = 2PR/(P + R)$.

In addition, we consider two other types of criteria that respectively account for the top-k predictions and the position (rank) of the correct article in predictions. The first aspect is captured in terms of the fraction of correct article labels that are found in the top-k predictions (i.e., top-k-probability results in response to each query), and averaging over all queries, which is the *recall@k* ($R@k$). The second aspect is measured as the *mean reciprocal rank* (MRR) considering for each query the rank of the correct prediction over the classification probability distribution, and averaging over all queries.

Moreover, we wanted to understand the *uncertainty of prediction* of LamBERTa models when evaluated over each query: to this purpose, we measured the *entropy* of the classification probability distributions obtained for each query evaluation, and averaged over all queries; in particular, we distinguished between the entropy of each entire distribution (E) from the entropy of the distribution corresponding to the top-k-probability results ($E@k$).

7.3.2 Multi-label evaluation context

The basic requirement for the multi-label evaluation context is that, for each test query, a set of articles is regarded as relevant to the query. In this respect, we consider two different perspectives, depending on whether a query is (i) originally associated with or derived from a particular article, or (ii) by-definition associated with a group of articles. We will refer to the former scenario as *article-driven* multi-label evaluation, and to the second scenario as *topic-driven* multi-label evaluation.

Article-driven multi-label evaluation. For this stage of evaluation, we require that, for each test query associated with article A_i, a set of articles *related* to A_i is to be selected as the set of articles relevant to the query, together with A_i. We adopt two approaches to determine the *article relatedness*, which rely on a supervised and an unsupervised grouping of the articles, respectively. The supervised approach refers to the logical organization of the articles of each book originally available in the ICC (cf. Sect. 3), whereas the unsupervised approach leverages a content-similarity-based grouping of the articles produced by a document clustering method.

ICC-classification-based. We exploit the ICC-provided classification meta-data of each book to label each article with the terminal division it belongs to. Since a division usually contains a few articles, the same label will be associated to multiple articles. It should be noted that the book hierarchies are quite different to each other, both in terms of maximum branching (e.g., from 5 chapters in Book-2 and Book-6, to 14 chapters in Book-1) and total number of divisions (e.g., from 51 in Book-2 to 135 in Book-4); moreover, sections, subchapters or even chapters can be leaf nodes in the corresponding hierarchy, i.e., they contain articles without any further division. This leads to the following distribution of number of labels over the various books: 50 in Book-1, 40 in Book-2, 47 in Book-3, 112 in Book-4, 94 in Book-5, 56 in Book-6.

Clustering-based. As concerns the unsupervised, similarity-based approach, we compute a clustering of the set of articles of a given book, so that each cluster will correspond to a group of articles that are similar by content. Each of the produced clusters will be regarded as the set of relevant articles for each query whose original label article belongs to that set. Therefore, if a cluster contains n articles, then each of the queries originally labeled with any of such n articles, will share the same set of n relevant articles.

To perform the clustering of the article set of a given book, we resort to a widely-used, well-known document clustering method, which consists in applying a centroid-based partitional clustering algorithm (Jain and Dubes 1988) over a document-term matrix modeling a vectorial bag-of-words representation of the documents over the term feature space, using TF-IDF (term-frequency inverse-document-frequency) as term relevance weighting function (Jones 2004) and cosine similarity for document comparison. This method is also known as *spherical k-means* (Dhillon and Modha 2001). We used a particularly effective and optimized version of this method, called bisecting k-means (Zhao and Karypis 2004), which is a standard de-facto of document clustering tools based on the classic bag-of-words model.[13]

It should be emphasized that our goal here is to induce an organization of the articles that is based on content affinity while discarding any information on the ICC article labeling. In this regard, we have deliberately exploited a representation model that, despite its known limitations in being unable to capture latent semantic aspects underlying correlations between words, it is still an effective baseline, yet unbiased with respect to the deep language model ability of LamBERTa.

Computation of relevant sets. Let us denote with $\mathcal{P}$ a partitioning of $\mathcal{C}$ that corresponds to either the ICC classification of the articles in $\mathcal{C}$ (i.e., supervised organization) or a clustering of $\mathcal{C}$ (i.e., unsupervised organization). For either approach, given a test query $q_i \in Q$ with article label A, we detect the relevant article set for q as the partition $P \in \mathcal{P}$ that contains A, then we match this set to the set of top-$|P|$ predictions of $\mathcal{M}$ to compute precision, recall, and F-measure for q_i. Finally, we averaged over all queries to obtain overall precision, recall, micro-averaged F-measure and macro-averaged F-measure.

Topic-driven multi-label evaluation. Unlike the previously discussed evaluation stage, here we consider queries that are expressed by one or few keywords describing the topic associated with a set of articles.

[13] http://glaros.dtc.umn.edu/gkhome/cluto/cluto/overview.

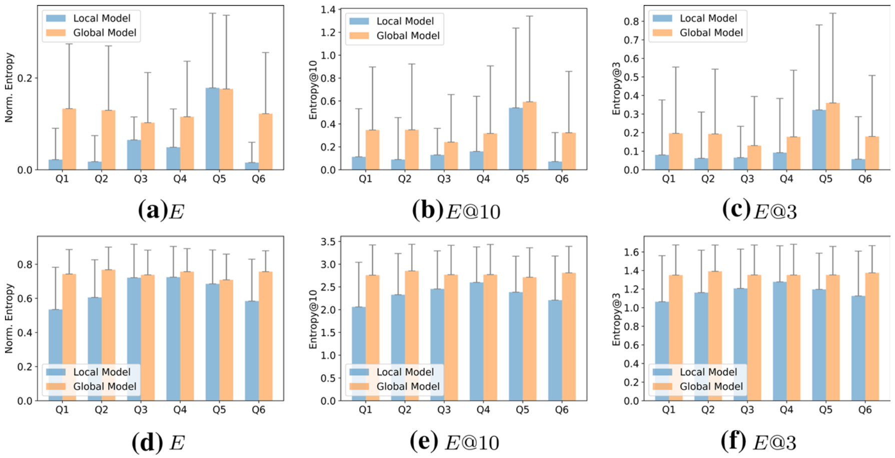
Table 4 Global vs. local models, for all sets of book-sentence-queries (QType-1, upper subtable), paraphrased-sentence-queries (QType-2, second upper subtable), comment-queries (QType-3, third upper subtable), comment-sentence-queries (QType-4, second bottom subtable), and case-queries (QType-5, bottom subtable): Recall, Precision, micro- and macro-averaged F-measures, Recall@k, and MRR

	R		P		F^{μ}		F^{M}		$R@3$		$R@10$		MRR	
i	L_i	G	L_i	G	L_i	G	L_i	G	L_i	G	L_i	G	L_i	G
Q_1	**0.962**	0.949	0.975	**0.979**	**0.961**	0.955	**0.969**	0.964	0.989	**0.992**	**0.999**	0.997	**0.976**	0.970
Q_2	**0.972**	0.954	0.981	**0.985**	**0.971**	0.961	**0.977**	0.969	**0.994**	0.981	**0.999**	0.986	**0.983**	0.968
Q_3	**0.990**	0.978	**0.994**	0.994	**0.990**	0.981	**0.992**	0.986	**1.000**	0.995	**1.000**	0.997	**0.995**	0.987
Q_4	**0.961**	0.948	0.983	**0.985**	**0.964**	0.958	**0.972**	0.966	**0.984**	0.977	**0.990**	0.986	**0.975**	0.966
Q_5	**0.910**	0.905	0.944	**0.947**	**0.909**	0.908	**0.927**	0.925	**0.984**	0.974	**0.998**	0.988	**0.947**	0.940
Q_6	**0.979**	0.961	**0.986**	0.986	**0.978**	0.966	**0.982**	0.973	**1.000**	0.985	**1.000**	0.992	**0.989**	0.974
Q_1	**0.841**	0.730	**0.866**	0.823	**0.828**	0.745	**0.853**	0.774	**0.905**	0.829	**0.949**	0.881	**0.881**	0.784
Q_2	**0.828**	0.639	**0.856**	0.766	**0.814**	0.669	**0.841**	0.697	**0.992**	0.742	**0.941**	0.812	**0.871**	0.701
Q_3	**0.861**	0.728	**0.886**	0.843	**0.851**	0.756	**0.873**	0.781	**0.922**	0.816	**0.942**	0.842	**0.896**	0.778
Q_4	**0.736**	0.635	**0.756**	0.706	**0.713**	0.639	**0.746**	0.668	**0.806**	0.716	**0.861**	0.783	**0.779**	0.685
Q_5	**0.718**	0.684	**0.759**	0.742	**0.710**	0.686	**0.738**	0.712	**0.843**	0.808	**0.908**	0.867	**0.790**	0.755
Q_6	**0.841**	0.704	**0.874**	0.817	**0.833**	0.730	**0.857**	0.756	**0.914**	0.783	**0.941**	0.845	**0.882**	0.756
Q_1	**0.349**	0.25	**0.248**	0.196	**0.274**	0.211	**0.290**	0.220	**0.494**	0.422	**0.675**	0.530	**0.455**	0.355
Q_2	**0.313**	0.177	**0.213**	0.145	**0.239**	0.155	**0.253**	0.159	**0.494**	0.307	**0.655**	0.441	**0.445**	0.265
Q_3	**0.396**	0.260	**0.298**	0.216	**0.325**	0.228	**0.340**	0.236	**0.577**	0.426	**0.704**	0.574	**0.507**	0.371
Q_4	**0.336**	0.247	**0.239**	0.190	**0.264**	0.206	**0.279**	0.215	**0.487**	0.387	**0.622**	0.522	**0.438**	0.343
Q_5	0.171	**0.252**	0.128	**0.190**	0.137	**0.205**	0.147	**0.216**	0.364	**0.433**	0.562	**0.590**	0.302	**0.375**
Q_6	**0.387**	0.235	**0.291**	0.178	**0.317**	0.193	**0.332**	0.203	**0.588**	0.388	**0.745**	0.551	**0.515**	0.340

Table 4 (continued)

	R		P		F^{μ}		F^{M}		$R@3$		$R@10$		MRR	
i	L_i	G	L_i	G	L_i	G	L_i	G	L_i	G	L_i	G	L_i	G
Q_1	**0.190**	0.136	**0.197**	0.183	**0.170**	0.135	**0.194**	0.156	**0.363**	0.265	**0.502**	0.376	**0.333**	0.239
Q_2	**0.216**	0.100	**0.191**	0.148	**0.173**	0.106	**0.203**	0.119	**0.343**	0.172	**0.473**	0.257	**0.315**	0.157
Q_3	**0.241**	0.153	**0.223**	0.188	**0.204**	0.145	**0.231**	0.169	**0.433**	0.268	**0.569**	0.405	**0.395**	0.250
Q_4	**0.189**	0.144	**0.176**	0.173	**0.156**	0.137	**0.182**	0.157	**0.324**	0.253	**0.450**	0.345	**0.293**	0.228
Q_5	0.092	**0.119**	0.132	**0.148**	0.090	**0.113**	0.108	**0.132**	0.256	**0.278**	0.414	**0.426**	0.222	**0.248**
Q_6	**0.224**	0.144	**0.211**	0.209	**0.192**	0.147	**0.218**	0.171	**0.372**	0.237	**0.508**	0.336	**0.333**	0.210
Q_1	**0.228**	0.118	**0.233**	0.121	**0.210**	0.101	**0.230**	0.120	**0.494**	0.304	**0.813**	0.488	**0.430**	0.263
Q_2	**0.292**	0.162	**0.316**	0.232	**0.274**	0.172	**0.303**	0.191	**0.501**	0.280	**0.726**	0.444	**0.465**	0.270
Q_3	**0.284**	0.190	**0.323**	0.217	**0.273**	0.180	**0.302**	0.203	**0.566**	0.330	**0.856**	0.474	**0.489**	0.286
Q_4	**0.259**	0.159	**0.299**	0.187	**0.250**	0.150	**0.278**	0.172	**0.528**	0.314	**0.803**	0.493	**0.458**	0.279
Q_5	**0.354**	0.256	**0.401**	0.307	**0.342**	0.252	**0.376**	0.279	**0.641**	0.484	**0.884**	0.647	**0.564**	0.426
Q_6	**0.392**	0.241	**0.445**	0.313	**0.372**	0.247	**0.417**	0.273	**0.665**	0.376	**0.885**	0.520	**0.590**	0.347

Bold values correspond to the best model for each query-set and evaluation criterion



(a) E **(b)** $E@10$ **(c)** $E@3$

(d) E **(e)** $E@10$ **(f)** $E@3$

Fig. 5 Global vs. local models, for all sets of book-sentence-queries (**a**–**c**) and comment-sentence-queries (**d**–**f**): Mean and standard deviation of the normalized Entropy and of the Entropy@k values of the classification probability distributions

To this purpose, we again exploit the meta-data of article organization available in the ICC books, so that the articles belonging to the same division of a book (i.e., chapter, subchapter, section) will be regarded as the set of articles relevant to the query corresponding to the description of that division. Depending on the choice of the type of a book's division, i.e., the level of the ICC-classification hierarchy of that book, a different query set will be produced for the book.

Given a test query $q_i \in Q$ with article labels $A_{i_1}, \ldots, A_{i_n}$, we match this set to the set of top-i_n predictions of $\mathcal{M}$ to compute precision, recall, and F-measure for q_i. Finally, we averaged over all queries to obtain overall precision, recall, micro-averaged F-measure and macro-averaged F-measure. Moreover, we measured the fraction of top-k predictions that are relevant to a query, and averaging over all queries, i.e., *precision*@k ($P@k$).

8 Results

We organize the presentation of results into three parts. Section 8.1 describes the comparison between global and local models under both the single-label and multi-label evaluation contexts; note that we will use notations G and L_i to refer to the global model and the local model corresponding to the i-th book, respectively, for any given test query-set. Section 8.2 is devoted to an ablation study of our models, focusing on the analysis of the various unsupervised data labeling methods and the effect of the training size on the models' performance. Finally, Sect. 8.3 presents results obtained by competing deep-learning methods.

8.1 Global vs. local models

8.1.1 Single-label evaluation

Table 4 and Fig. 5 compare global and local models, for all books of the ICC, according to the criteria selected for the single-label evaluation context. For the sake of brevity yet representativeness, here we show results corresponding to the `UniRR.T`$^+$ labeling scheme—as we shall discuss in Sect. 8.2, this choice of training-instance labeling scheme is justified as being in general the best-performing scheme for the query sets; nonetheless, analogous findings were drawn by using other types of queries and labeling schemes.

Looking at the table, let us first consider the results obtained by the LamBERTa models against QType-1 queries. At a first sight, we observe the outstanding scores achieved by all models; this was obviously expected since QType-1 queries are directly extracted from sentences of the book articles used to train the models. More interesting is the comparison between the local models and the global model: for any query-set from the *i*-th book, the corresponding local model behaves significantly better than the global model in most cases. It should be noticed that the slightly better results of the global model in terms of precision are actually determined by its occasional wrongly predictions of articles from different books in place of articles of Book-*i*.

The outperformance of local models over the global one is also confirmed in terms of the entropy results, which are always lower, and hence better, than the global's ones. Moreover, while the plots in Fig. 5 are representative for QType-1 and QType-4 queries, the above result for the comparison between local and global models in terms of entropy behavior equally holds regardless of the type of query set. Note that, in Fig. 5a and (d), the values of entropy are normalized within the interval [0, 1] to get a fair comparison between the local models and global models.[14] This indicates that the predictions made by a local model are generally more certain than those by the global model.

Turning back to the results reported in Table 4, we observe that high performance scores are still obtained for the paraphrased-sentence-based queries, which indicates a remarkable robustness of LamBERTa models w.r.t. lexical variants of queries.

Considering now the comment-based queries, both in the paragraph-size (i.e., QType-3) and sentence-size versions (i.e., QType-4), we observe a much lower performance of the models. This is nonetheless not surprising since QType-3 and QType-4 queries are lexically and linguistically different from the ICC contents (cf. Sect. 7.2). Besides that, local models show to be consistently better than the global ones, despite the cross-corpora learning ability of the global model which, in principle, could be beneficial for queries that may contain references to articles of different books. One exception corresponds to Book-5: as confirmed by a qualitative

[14] For each book, the entropy value of the local model is divided by the base-2 logarithm of the number of articles of that book, whereas the entropy value of the global model is always divided by the base-2 logarithm of the total number of articles in the ICC.

Table 5 Article-driven, Clustering-based multi-label evaluation: global vs. local models, with labeling scheme `UniRR.T`$^+$, for all sets of book-sentence-queries (QType-1), paraphrased-sentence-queries (QType-2), comment-queries (QType-3), comment-sentence-queries (QType-4), and case-queries (QType-5). (Bold values correspond to the best model for each query-set and evaluation criterion)

Query-set		R		P		F^μ		F^M	
	i	L_i	G	L_i	G	L_i	G	L_i	G
QType-1	Q_1	**0.615**	0.592	**0.617**	0.591	**0.615**	0.591	**0.616**	0.591
	Q_2	**0.674**	0.636	**0.684**	0.640	**0.676**	0.637	**0.679**	0.638
	Q_3	**0.623**	0.604	**0.626**	0.603	**0.624**	0.603	**0.625**	0.603
	Q_4	**0.331**	0.313	**0.326**	0.312	**0.324**	0.312	**0.328**	0.312
	Q_5	0.631	**0.632**	0.633	**0.634**	0.628	**0.631**	0.632	**0.633**
	Q_6	**0.711**	0.675	**0.720**	0.677	**0.710**	0.675	**0.715**	0.676
QType-2	Q_1	**0.557**	0.473	**0.559**	0.474	**0.557**	0.472	**0.558**	0.473
	Q_2	**0.595**	0.442	**0.604**	0.445	**0.598**	0.443	**0.599**	0.444
	Q_3	**0.563**	0.477	**0.566**	0.479	**0.563**	0.477	**0.564**	0.478
	Q_4	0.172	**0.236**	0.213	**0.237**	0.186	**0.236**	0.190	**0.237**
	Q_5	**0.522**	0.498	**0.526**	0.499	**0.522**	0.497	**0.524**	0.498
	Q_6	**0.624**	0.511	**0.628**	0.512	**0.625**	0.511	**0.626**	0.513
QType-3	Q_1	**0.312**	0.241	**0.315**	0.242	**0.312**	0.241	**0.313**	0.242
	Q_2	**0.296**	0.164	**0.300**	0.165	**0.297**	0.164	**0.298**	0.164
	Q_3	**0.332**	0.226	**0.337**	0.228	**0.333**	0.226	**0.334**	0.227
	Q_4	**0.234**	0.174	**0.241**	0.175	**0.236**	0.174	**0.237**	0.174
	Q_5	0.209	**0.249**	0.214	**0.252**	0.209	**0.250**	0.211	**0.251**
	Q_6	**0.361**	0.234	**0.365**	0.236	**0.361**	0.234	**0.363**	0.235
QType-4	Q_1	**0.227**	0.154	**0.227**	0.155	**0.226**	0.154	**0.227**	0.154
	Q_2	**0.205**	0.098	**0.207**	0.103	**0.205**	0.096	**0.206**	0.100
	Q_3	**0.259**	0.153	**0.261**	0.154	**0.258**	0.153	**0.260**	0.153
	Q_4	**0.163**	0.123	**0.164**	0.127	**0.164**	0.123	**0.163**	0.125
	Q_5	0.151	**0.172**	0.152	**0.179**	0.150	**0.174**	0.151	**0.175**
	Q_6	**0.236**	0.147	**0.238**	0.149	**0.235**	0.147	**0.237**	0.148
QType-5	Q_1	**0.283**	0.179	**0.289**	0.183	**0.284**	0.180	**0.286**	0.181
	Q_2	**0.294**	0.170	**0.304**	0.175	**0.298**	0.172	**0.299**	0.173
	Q_3	**0.298**	0.171	**0.302**	0.174	**0.299**	0.171	**0.300**	0.172
	Q_4	**0.274**	0.192	**0.276**	0.193	**0.275**	0.191	**0.275**	0.192
	Q_5	**0.378**	0.296	**0.382**	0.298	**0.378**	0.295	**0.380**	0.297
	Q_6	**0.404**	0.226	**0.408**	0.229	**0.405**	0.226	**0.406**	0.227

inspection of the legal experts who assisted us, this is due to an accentuation in the queries for Book-5 of a tendency in more broadly covering subjects of articles from other books. This is also supported by quantitative statistics about the uniqueness of the terms in the vocabulary of a book: in fact, we found out that the percentage of a book's vocabulary terms that are unique is minimum w.r.t. Book-5; in detail, 39% of Book-1 and Book-2, 48% of Book-3, 43% of Book-4, and 36% of Book-6. A

Table 6 Article-driven, ICC-classification-based multi-label evaluation: global vs. local models, with labeling scheme `UniRR.T`$^+$, for all sets of book-sentence-queries (QType-1), paraphrased-sentence-queries (QType-2), comment-queries (QType-3), comment-sentence-queries (QType-4), and case-queries (QType-5)

Query-set		R		P		F^μ		F^M	
	i	L_i	G	L_i	G	L_i	G	L_i	G
QType-1	Q_1	**0.247**	0.220	**0.312**	0.269	**0.268**	0.236	**0.276**	0.242
	Q_2	**0.198**	0.187	**0.256**	0.237	**0.216**	0.203	**0.223**	0.209
	Q_3	**0.217**	0.192	**0.287**	0.250	**0.238**	0.209	**0.247**	0.217
	Q_4	**0.191**	0.179	**0.234**	0.217	**0.205**	0.191	**0.210**	0.196
	Q_5	**0.201**	0.191	**0.253**	0.240	**0.218**	0.207	**0.224**	0.213
	Q_6	**0.268**	0.243	**0.306**	0.283	**0.279**	0.254	**0.286**	0.262
QType-2	Q_1	**0.244**	0.194	**0.310**	0.239	**0.265**	0.209	**0.273**	0.214
	Q_2	**0.215**	0.160	**0.278**	0.200	**0.235**	0.173	**0.246**	0.178
	Q_3	**0.206**	0.164	**0.280**	0.224	**0.229**	0.182	**0.238**	0.189
	Q_4	**0.172**	0.144	**0.213**	0.178	**0.186**	0.156	**0.190**	0.159
	Q_5	**0.186**	0.168	**0.235**	0.213	**0.202**	0.183	**0.208**	0.188
	Q_6	**0.257**	0.212	**0.297**	0.248	**0.268**	0.222	**0.276**	0.228
QType-3	Q_1	**0.245**	0.167	**0.319**	0.215	**0.269**	0.183	**0.277**	0.188
	Q_2	**0.170**	0.096	**0.239**	0.134	**0.192**	0.108	**0.199**	0.112
	Q_3	**0.189**	0.133	**0.265**	0.186	**0.212**	0.149	**0.220**	0.155
	Q_4	**0.169**	0.126	**0.215**	0.161	**0.184**	0.138	**0.189**	0.141
	Q_5	**0.154**	0.146	**0.204**	0.200	**0.169**	0.165	**0.176**	0.169
	Q_6	**0.240**	0.167	**0.285**	0.211	**0.252**	0.178	**0.261**	0.186
QType-4	Q_1	**0.188**	0.122	**0.241**	0.153	**0.205**	0.132	**0.211**	0.136
	Q_2	**0.123**	0.065	**0.174**	0.090	**0.139**	0.073	**0.144**	0.076
	Q_3	**0.156**	0.094	**0.230**	0.133	**0.176**	0.105	**0.184**	0.110
	Q_4	**0.126**	0.094	**0.164**	0.122	**0.139**	0.103	**0.142**	0.106
	Q_5	**0.118**	0.115	**0.188**	0.176	**0.140**	0.134	**0.145**	0.139
	Q_6	**0.173**	0.116	**0.204**	0.143	**0.182**	0.123	**0.187**	0.129
QType-5	Q_1	**0.309**	0.199	**0.381**	0.237	**0.334**	0.212	**0.341**	0.216
	Q_2	**0.193**	0.110	**0.265**	0.151	**0.215**	0.122	**0.223**	0.127
	Q_3	**0.244**	0.167	**0.274**	0.179	**0.255**	0.172	**0.258**	0.173
	Q_4	**0.233**	0.158	**0.296**	0.199	**0.254**	0.172	**0.261**	0.176
	Q_5	**0.214**	0.174	**0.272**	0.224	**0.234**	0.191	**0.240**	0.196
	Q_6	**0.245**	0.159	**0.276**	0.185	**0.253**	0.165	**0.259**	0.171

Bold values correspond to the best model for each query-set and evaluation criterion

further interesting remark can be drawn from the comparison of the QType-3 scores with the QType-4 scores, as these appear to be generally higher for the former queries, which provide more topical context than sentence-size queries. This would hence suggest that relatively long queries can be handled by LamBERTa models effectively.

Notably, the above finding on the ability of handling long, contextualized queries is also confirmed by inspectioning the results obtained against the queries stating case law decisions (i.e., QType-5 queries). Indeed, despite the particular difficulty of such a testbed, LamBERTa models show performance scores that are generally comparable to those obtained for the QType-3 comment queries; moreover, once again, local models behave better than the corresponding global ones, according to all assessment criteria (and even without exceptions as opposed to QType-3 comment queries).

8.1.2 Multi-label evaluation

Our investigation on the effectiveness of global and local models was further deepened under the different multi-label evaluation contexts we devised.

Article-driven multi-label evaluation. Tables 5 and 6 report results according to the article-driven clustering-based and ICC-classification-based analyses, respectively. For the clustering-based approach, results correspond to a number of clusters over the articles of each book that was set so to have mean cluster size close to three.

At a first glance, the superiority of local models stands out, thus confirming the findings drawn from the single-label evaluation results. Upon a focused inspection, we observe few exceptions in Table 5 corresponding to results on Book-5 (similarly as we already found in Table 4) for the QType-1, QType-3, and QType-4, and on Book-4 for QType-2; however, this does not occur in Table 6. We tend to ascribe this to the fact that, being driven by a content-similarity-based approach, the clustering of the articles is clearly conditioned on the higher topic variety observable in Book-5 or Book-4, which may favor a global model against a local one in better capturing topics that are outside the boundaries of that particular book. By contrast, this does not hold for the ICC-classification-based grouping of the articles, as it relies on an externally provided organization of the articles in a particular book that is not constrained by the topic patterns (e.g., word co-occurrences) that might be distinctive of that book.

Notably, looking at the QType-5 results, the performance scores obtained by local and global models are generally comparable to or even higher than those respectively obtained on QType-3 (or QType-4) queries, which is particularly evident for the ICC-classification-based grouping of the articles (Table 6).

As a further point of investigation, we explored whether the article-driven clustering-based multi-label evaluation is sensitive to how the query relevant sets (i.e., clusters of articles) were formed, with a focus on the content representation model of the articles. In particular, we replaced the TF-IDF vectorial representation of the articles with the article embeddings generated by our LamBERTa models, while keeping the same clustering methodology and setting as used in our previous analysis. From the comparison results reported in the Appendix, Table 13, it stands out that using the embeddings generated by LamBERTa models to represent the articles in the clustering process is always beneficial to the multi-label classification performance of LamBERTa local models, according to all criteria and query sets. As expected, the improvements are generally more evident for QType-1 and QType-2 query sets, since these queries have lexicons close to the training data. More

Table 7 Topic-driven multi-label evaluation: global vs. local models, with labeling scheme `UniRR.T`$^{+}$, for all sets of ICC-heading-queries (i.e., QType-6 query sets). Column ‘a_cs’ stands for average class size, i.e., the average no. of articles belonging to each query label

	Chapter					Subchapter					Section				
i	a_cs	F^{μ}		$P@3$		a_cs	F^{μ}		$P@3$		a_cs	F^{μ}		$P@3$	
		L_i	G	L_i	G		L_i	G	L_i	G		L_i	G	L_i	G
Q_1	26.1	**0.314**	0.251	**0.867**	0.733	14.4	**0.307**	0.253	**0.875**	0.792	7.5	**0.348**	0.205	**0.722**	0.556
Q_2	69.0	**0.256**	0.247	0.800	0.800	11.6	**0.167**	0.145	**0.519**	0.370	11.8	**0.234**	0.089	**0.500**	0.333
Q_3	40.3	**0.287**	0.225	**0.667**	0.556	17.6	**0.185**	0.145	**0.778**	0.389	8.5	**0.270**	0.219	**0.577**	0.500
Q_4	98.4	**0.238**	0.083	**0.444**	0.333	17.1	**0.216**	0.144	**0.673**	0.531	8.3	**0.218**	0.149	**0.653**	0.531
Q_5	64.8	**0.174**	0.163	0.545	**0.727**	22.2	**0.263**	0.237	0.733	0.733	10.9	0.215	**0.219**	**0.558**	0.512
Q_6	66.2	**0.402**	0.198	**1.000**	0.600	21.4	**0.319**	0.202	**0.667**	0.467	6.5	**0.290**	0.248	**0.571**	0.486

Bold values correspond to the best model for each query-set and evaluation criterion interestingly, we also observe that the performance gain by LamBERTa embeddings tends to be higher for the largest books, i.e., Book-4 and Book-5, with peaks of about 300% percentage increase reached with the QType-2 query-set relevant for Book-4. Nonetheless, apart from these particular cases, discovering clusters over a set of articles represented by their LamBERTa embeddings does not bring in general to outstanding boost of performance against the TF-IDF vectorial representation: indeed, this can be ascribed to the very small size of the clusters produced, and hence the TF-IDF vectorial representation can well approximate and match the clusters detected over the LamBERTa embeddings of the articles, especially in smaller collections of articles (i.e., ICC books).

Topic-driven multi-label evaluation. Let us now focus on the topic-driven multi-label evaluation results, based on QType-6 queries, which are shown in Table 7 (details on precision and recall values are omitted for the sake of presentation, but this does not change the remarks being discussed). Three major remarks arise here. The first one is again about the higher effectiveness of local models against the global one, for each of the book query-sets, with the usual exception corresponding to Book-5, which is more evident as the type of division is finer-grain. The second remark concerns a comparison between the methods' performance by varying the types of book division: the chapter, subchapter and section cases are indeed quite different to each other, which should be noticed through the different values of the average number of articles "covered" by each query label-class; in general, higher values correspond to more abstract divisions. Moreover, the roughly monotone variation of this statistic over all books cannot be coupled with a monotonic variation of the performances: for instance, the highest F-measure values correspond to the division at section level in Book-1, whereas they correspond to the chapter level in Books-2, 3, 4 and 6. Finally, it is worth noticing that the performances significantly increase when precision@3 scores are considered, often reaching very high values: this would suggest that, despite the intrinsic complexity of this evaluation task, the models are able to guarantee a high fraction of top-3 predictions that correspond to the articles that are relevant for each query.

8.2 Ablation study

8.2.1 Training-instance labeling schemes

Besides the settings of BERT learning parameters, our LamBERTa models are expected to work differently depending on the choice of training-instance labeling scheme (cf. Sect. 4.5). Understanding how this aspect relates to the performance is fundamental, as it impacts on the complexity of the induced model. In this respect, we compared our defined labeling schemes, using the induced local models of Book-2 (i.e., L_2) as case in point.

Table 8 shows single-label evaluation results for all types of query-sets. As expected, we observe that the scheme based on an article's title only is largely the worst-performing method (with the exception of QType-2 where, due to the little

Table 8 Evaluation of different local models L_2 for all types of query-sets pertinent to articles of Book-2. (Bold values correspond to the best model for each query-set and evaluation criterion)

query-set	method	*R*	*P*	F^μ	F^M	*R*@10	*MRR*	*E*	*E*@10
QType-1	T	0.530	0.855	0.623	0.655	0.619	0.564	3.023	1.335
	UniRR	0.675	0.928	0.755	0.782	0.851	0.744	0.343	0.167
	BiRR	0.552	0.775	0.621	0.645	0.745	0.635	0.790	0.342
	TriRR	0.584	0.763	0.637	0.661	0.801	0.674	1.149	0.455
	CasRR	0.555	0.901	0.653	0.687	0.712	0.608	1.422	0.808
	TglRR	0.900	0.955	0.910	0.927	0.980	0.929	0.459	0.281
	UniRR.T$^+$	**0.972**	**0.981**	**0.971**	**0.977**	**0.999**	**0.983**	**0.149**	**0.089**
	CasRR.T$^+$	0.823	0.929	0.843	0.873	0.903	0.853	0.863	0.457
	TglRR.T$^+$	0.919	0.972	0.927	0.945	0.977	0.940	0.492	0.298
QType-2	T	0.410	0.598	0.456	0.487	0.551	0.463	3.892	1.706
	UniRR	0.549	0.744	0.605	0.632	0.754	0.624	**1.310**	**0.585**
	BiRR	0.342	0.470	0.374	0.396	0.581	0.436	2.084	0.899
	TriRR	0.442	0.620	0.494	0.516	0.699	0.544	2.253	0.881
	CasRR	0.383	0.620	0.444	0.473	0.597	0.455	2.289	1.232
	TglRR	0.612	0.722	0.626	0.662	0.823	0.684	2.101	1.107
	UniRR.T$^+$	**0.828**	**0.856**	**0.814**	**0.841**	**0.941**	**0.871**	1.620	0.732
	CasRR.T$^+$	0.625	0.740	0.639	0.677	0.784	0.685	2.221	1.074
	TglRR.T$^+$	0.632	0.729	0.642	0.677	0.854	0.705	2.311	1.174
QType-3	T	0.023	0.008	0.010	0.012	0.171	0.073	6.312	2.816
	UniRR	0.296	0.208	0.230	0.244	0.618	0.425	4.368	2.051
	BiRR	0.212	0.140	0.156	0.169	0.494	0.321	5.185	2.349
	TriRR	0.194	0.113	0.133	0.143	0.478	0.295	5.885	2.523
	CasRR	0.110	0.075	0.082	0.089	0.363	0.199	**4.034**	**1.800**
	TglRR	0.261	0.186	0.203	0.217	0.624	0.394	4.048	1.939
	UniRR.T$^+$	**0.313**	**0.213**	**0.239**	**0.253**	**0.655**	**0.445**	4.938	2.266
	CasRR.T$^+$	0.232	0.157	0.176	0.187	0.525	0.339	4.717	2.172
	TglRR.T$^+$	0.217	0.162	0.173	0.185	0.593	0.347	4.254	2.100
QType-4	T	0.037	0.042	0.028	0.039	0.137	0.076	6.379	2.800
	UniRR	0.175	0.199	0.160	0.186	0.439	0.271	4.000	1.834
	BiRR	0.104	0.125	0.094	0.114	0.309	0.185	4.592	2.065
	TriRR	0.090	0.101	0.077	0.096	0.275	0.163	5.357	2.241
	CasRR	0.056	0.068	0.049	0.061	0.219	0.115	**3.268**	**1.615**
	TglRR	0.154	0.178	0.141	0.165	0.416	0.253	4.174	1.991
	UniRR.T$^+$	**0.216**	0.191	**0.173**	**0.203**	**0.473**	**0.315**	5.077	2.311
	CasRR.T$^+$	0.135	0.161	0.119	0.147	0.347	0.211	4.586	2.130
	TglRR.T$^+$	0.144	**0.202**	0.143	0.168	0.398	0.226	4.148	2.027

Table 8 (continued)

query-set	method	R	P	F^{μ}	F^{M}	$R@10$	MRR	E	$E@10$
QType-5	`T`	0.036	0.025	0.022	0.029	0.127	0.081	6.570	2.968
	`UniRR`	0.260	0.288	0.232	0.273	0.666	0.436	**4.446**	**2.074**
	`BiRR`	0.232	0.236	0.197	0.234	0.548	0.357	4.873	2.198
	`TriRR`	0.225	0.248	0.204	0.236	0.568	0.380	5.498	2.408
	`CasRR`	0.082	0.089	0.068	0.086	0.334	0.187	5.429	2.400
	`TglRR`	0.278	**0.318**	0.258	0.297	0.686	0.434	4.560	2.150
	`UniRR.T`$^{+}$	**0.292**	0.316	**0.274**	**0.303**	**0.726**	**0.465**	4.972	2.299
	`CasRR.T`$^{+}$	0.238	0.295	0.233	0.263	0.579	0.380	4.822	2.158
	`TglRR.T`$^{+}$	0.283	0.316	0.273	0.299	0.700	0.463	4.638	2.137

Table 9 Single-label evaluation of local model L_2 `UniRR.T` $^{+}$with *minTU* = 64, for each type of query-set

query-set	R	P	F^{μ}	F^{M}	$R@10$	MRR	E	$E@10$
QType-1	0.971	0.982	0.971	0.977	0.996	0.982	0.090	0.072
	– 0.10%	+ 0.13%	**– 0.04%**	**– 0.04%**	**– 0.34%**	**– 0.13%**	– 39.40%	– 19.41%
QType-2	0.797	0.825	0.781	0.811	0.928	0.845	1.266	0.657
	– 3.73%	**– 3.67%**	**– 4.09%**	**– 3.62%**	**– 1.43%**	**– 2.97%**	– 21.85%	– 10.30%
QType-3	0.351	0.254	0.280	0.295	0.666	0.481	3.661	1.814
	+ 12.14%	+ 19.25%	+ 17.15%	+ 16.60%	+ 1.68%	+ 8.09%	– 25.86%	– 19.95%
QType-4	0.221	0.204	0.185	0.212	0.482	0.308	3.889	1.928
	+ 2.31%	+ 7.37%	+ 6.94%	+ 4.95%	+ 2.55%	**– 0.96%**	– 23.40%	– 16.57%
QType-5	0.342	0.352	0.320	0.347	0.740	0.460	3.615	1.872
	+ 17.13%	+ 11.33%	+ 16.67%	+ 14.53%	+ 1.93%	**– 1.08%**	– 27.27%	– 18.58%

Percentage values correspond to the increase/decrease percentage of performance criteria when using *minTU* = 64 compared to *minTU* = 32. (Highlighted in bold are the values corresponding to a worsening when using *minTU* = 64)

impact of paraphrasing on the article titles, it happens that the performance of `T` is slightly better than `CasRR`). More interestingly, lower size of *n*-gram seems to be beneficial to the effectiveness of the model, especially on QType-3, QType-4, and QType-5 queries, indeed `UniRR` always outperforms both `BiRR` and `TriRR`; also, `UniRR` behaves better than the cascade scheme (`CasRR`) as well, and again the gap is more evident in the comment-based queries. The combination of *n*-grams of varying size reflected by the `TglRR` scheme leads to a significant increase in the performance over all previously mentioned schemes, for QType-1, QType-2, and QType-5 queries. This would suggest that more sophisticated labeling schemes can lead to higher effectiveness in the learned model. Nonetheless, superior performance

Table 10 Multi-label evaluation of local model L_2 `UniRR.T`$^+$ with *minTU* = 64, for each type of query-set

Query-set	Clustering-based				ICC-Classification-based			
	R	P	F^μ	F^M	R	P	F^μ	F^M
QType-1	0.658	0.668	0.662	0.663	0.197	0.252	0.215	0.221
	– 2.08%	**– 2.20%**	**– 2.07%**	**– 2.21%**	**– 0.51%**	**– 1.56%**	**– 0.46%**	**– 0.90%**
QType-2	0.556	0.565	0.559	0.560	0.198	0.252	0.215	0.222
	– 6.55%	**– 6.46%**	**– 6.52%**	**– 6.51%**	**– 8.04%**	**– 9.34%**	**– 8.45%**	**– 8.61%**
QType-3	0.322	0.327	0.324	0.324	0.166	0.228	0.185	0.192
	+8.78%	+9.00%	+9.09%	+8.72%	**– 2.35%**	**– 4.60%**	**– 3.65%**	**– 3.52%**
QType-4	0.202	0.206	0.203	0.204	0.131	0.183	0.148	0.153
	– 0.98%	+0.00%	**– 0.98%**	**– 0.49%**	+6.50%	+5.17%	+6.47%	+6.25%
QType-5	0.312	0.327	0.319	0.320	0.181	0.247	0.201	0.209
	+6.04%	+7.72%	+7.12%	+7.09%	**– 6.22%**	**– 6.79%**	**– 6.51%**	**– 6.28%**

Percentage values correspond to the increase/decrease percentage of performance criteria when using *minTU* = 64 compared to *minTU* = 32. (Highlighted in bold are the values corresponding to a worsening when using *minTU* = 64)

is obtained by considering the schemes with emphasis on the title, which all improve upon the corresponding schemes not emphasizing the title, with `UniRR.T`$^+$ being the best-performing method by far according to all criteria.

It also should be noted that the comment and case law query testbeds confirmed to be more difficult than the other types of queries. Also, QType-3 and QType-5 results are found to be generally higher than those obtained for QType-4 queries, which would indicate that, by providing a more informative context, long (i.e., paragraph-like) queries are better handled by LamBERTa models w.r.t. their shorter (i.e., sentence-like) counterparts.

8.2.2 Training units per article

The setting of the number of training units per article (*minTU*, whose default is 32), which impacts on the size of the training sets, is another model parameter that in principle deserves attention. We investigated this aspect according to both single-label and multi-label evaluation contexts, whose results are reported in Table 9 and Table 10, respectively, for the local model learned from Book-2; note that, once again, this is for the sake of presentation, as we found out analogous remarks for other books.

Our goal was to understand whether and to what extent doubling the *minTU* value could lead to improve the model performance. In this respect, considering the single-label evaluation case, we observe two different outcomes when setting *minTU* to 64: the one corresponding to QType-1 and QType-2 queries, which unveils a general degradation of the performance, and the other one corresponding to QType-3, QType-4, QType-5 queries, which conversely shows significant improvements according to most criteria. This is remarkable as it would suggest that increasing the number of replicas in building the books' training sets is unnecessary, or even detrimental, for queries lexically close to the book articles; by contrast, it turns out to be useful for improving the classifier performance against more difficult query-testbeds like comment and case queries. Looking at the multi-label evaluation results, we can draw analogous considerations for the clustering-based evaluation approach (since results over QType-4 are only slightly decreased), whereas using less training replicas appears to be preferable for the ICC-classification-based evaluation approach.

8.3 Comparative analysis

8.3.1 Text-based law article prediction

We conducted a comparative analysis of LamBERTa models with state-of-the-art text classifiers based on deep learning architectures:

- *BiLSTM* (Liu et al. 2016; Zhou et al. 2016), a bidirectional LSTM model as sequence encoder. LSTM models have been widely used in text classification as they can capture contextual information while representing the sentence by fixed size vector. The model exploited in this evaluation utilizes 2 layers of BiLSTM, with 32 hidden units for each BiLSTM layer.
- *TextCNN* (Kim 2014), a convolutional-neural-network-based model with multiple filter widths for text encoding and classification. Every sentence is represented as a bidimensional tensor of shape (n, d), where n is the sentence length and d is the dimensionality of the word embedding vectors. The *TextCNN* model utilizes three different filter windows of sizes $\{3, 4, 5\}$, 100 feature maps for the windows' sizes, ReLU activation function and max-pooling.
- *TextRCNN* (Lai et al. 2015), a bidirectional LSTM with a pooling layer on the last sequence output. *TextRCNN* therefore combines the recurrent neural network and convolutional network to leverage the advantages of the individual models in capturing the text semantics. The model first exploits a recurrent structure to learn word representations for every word in the text, thus capturing the contextual information; afterwards, max-pooling is applied to determine which features are important for the classification task.
- *Seq2Seq-A* (Du and Huang 2018; Bahdanau et al. 2015), a Seq2Seq model with attention mechanism. Seq2Seq models have been widely used in machine translation and document summarization due to their capability to generate new sequences based on observed text data. For text classification, here the *Seq2Seq-A* model utilizes a single layer BiLSTM as encoder with 32 hidden units. This encoder learns the hidden representation for every word in an input sentence, and its final state is then used to learn attention scores for each word in the sentence. After learning the attention weights, the weighted sum of encoder hidden states (hidden states of words) gives the attention output vector. The latter is then concatenated to the hidden representation and passed to a linear layer to produce the final classification.

- *Transformer* model for text classification, which is adapted from the model originally proposed for the task of machine translation in Vaswani et al. (2017). The key aspect in this model is the use of an attention mechanism to deal with long range dependencies, but without resorting to RNN models. The encoder part of the original Transformer model is used for classification. This encoder is composed of 6 layers, each having two sub-layers, namely a multi-head attention layer, and a 2-layer feed-forward network. Compared to BERT, residual connection, layer normalization, and masking are discarded.

Evaluation requirements. We designed this comparative evaluation to fulfill three main requirements: (i) significance of the selected competing methods, (ii) robustness of their evaluation, and (iii) relatively fair comparison among the competing methods and our LamBERTa models.

To meet the first requirement, we focused on deep neural network models that have been widely used for text classification and are often referred to as "predecessors" of deep pre-trained language models like BERT.

To ensure a robust evaluation, we carried out an extensive parameter-tuning phase of each competing methods, by varying all main parameters within recommended or reasonable range values, which include: dropout probability (within [0.1,0.4]), maximum sentence length (fixed to 60, or flexible), batch size (base-2 powers from 16 to 128), number of epochs (from 10 to 100). The results we will present here refer to the best performances achieved by each of the models.

We considered main aspects that are shared between our models and the competing ones to achieve a fair comparison. First, as each of the competing models, except the Transformer, needs word vector initialization, they were provided with Italian Wikipedia pre-trained Glove embeddings—recall that Italian Wikipedia is a major constituent of the pre-trained Italian BERT used for our LamBERTa models. Each model was then fine-tuned over the individual ICC books following the same data labeling schemes used for the LamBERTa models. Moreover, since we have to train a classification problem with as many classes as the number of articles for a given ICC book, all the models use an appropriate yet identical setting as in LamBERTa for the optimizer (i.e., Adam) and the loss function (i.e., cross entropy).

Experimental results. The goal of this evaluation stage was to demonstrate the superiority of LamBERTa against the selected competitors for case law retrieval as classification task, using different types of test queries. For each competitor, we used the individual books' `UniRR.T`$^{+}$ labeled data for training. We carried out several runs by varying the main parameters as previously discussed, and eventually, we selected the best-performing results for each competitor and query-set, which are shown in Table 11.

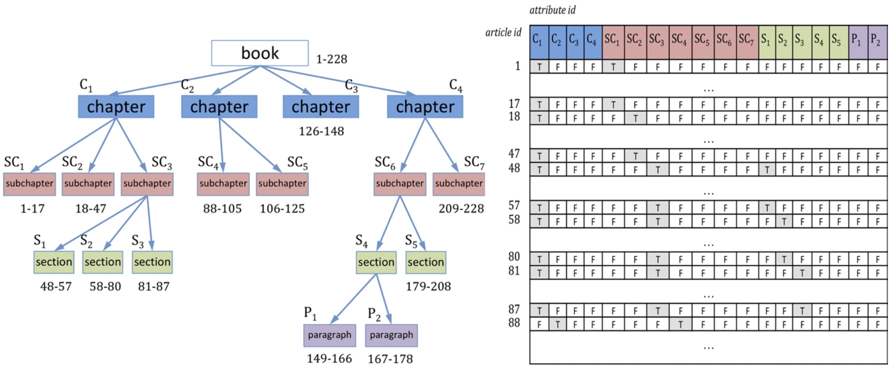
Looking at the table, there are a few remarks that stand out about the competitors. First, the *Transformer* model consistently excels over the other competitors in QType-1 and QType-2 query sets; this hints at a better effectiveness of the *Transformer* approach against queries that have some lexical affinity with the training text data. By contrast, when this does not hold as for comment (i.e., QType-4) and case law (i.e., QType-5) queries, *TextCNN* and *TextRCNN* tend to perform better than the

Table 11 Competing models trained with the individual ICC books annotated with the `UniRR.T`$^+$ labeling scheme, and tested over all sets of book-sentence-queries (QType-1, upper subtable), paraphrased-sentence-queries (QType-2, second upper subtable), comment-sentence-queries (QType-4, third upper subtable), and case-queries (QType-5, bottom subtable): best-performing values of precision, recall, and micro-averaged F-measure. (Bold values correspond to the best performance obtained by a competing method, for each query-set and evaluation criterion; LamBERTa performance values, formatted in italic, are also reported from Table 4 to ease the comparison with the competing methods)

	LamBERTa			*TextCNN*			*BiLSTM*			*TextRCNN*			*Seq2Seq-A*			*Transformer*		
i	P	R	F^μ	P	R	F^μ	P	R	F^μ	P	R	F^μ	P	R	F^μ	P	R	F^μ
Q_1	*0.975*	*0.962*	*0.961*	0.942	0.911	0.910	0.752	0.712	0.680	0.894	0.838	0.835	0.620	0.629	0.564	**0.959**	**0.950**	**0.948**
Q_2	*0.981*	*0.972*	*0.971*	0.959	0.940	0.936	0.735	0.730	0.681	0.894	0.852	0.845	0.630	0.670	0.585	**0.965**	**0.955**	**0.954**
Q_3	*0.994*	*0.990*	*0.990*	0.962	0.951	0.951	0.727	0.724	0.674	0.905	0.865	0.861	0.631	0.641	0.573	**0.970**	**0.965**	**0.965**
Q_4	*0.983*	*0.961*	*0.964*	0.971	0.933	0.938	0.789	0.772	0.736	0.919	0.875	0.872	0.727	0.703	0.665	**0.969**	**0.947**	**0.951**
Q_5	*0.944*	*0.910*	*0.909*	0.895	0.857	0.848	0.689	0.670	0.626	0.817	0.763	0.750	0.669	0.646	0.602	**0.936**	**0.903**	**0.903**
Q_6	*0.986*	*0.979*	*0.978*	0.949	0.938	0.935	0.745	0.723	0.677	0.903	0.866	0.858	0.757	0.718	0.685	**0.955**	**0.957**	**0.956**
Q_1	*0.866*	*0.841*	*0.828*	0.800	0.769	0.750	0.360	0.412	0.349	0.674	0.646	0.619	0.345	0.381	0.324	**0.801**	**0.774**	**0.754**
Q_2	*0.856*	*0.828*	*0.814*	0.760	0.726	0.706	0.409	0.442	0.382	0.646	0.643	0.601	0.353	0.384	0.327	**0.813**	**0.787**	**0.762**
Q_3	*0.886*	*0.861*	*0.851*	0.817	0.765	0.758	0.464	0.493	0.435	0.707	0.672	0.648	0.361	0.409	0.342	**0.852**	**0.804**	**0.795**
Q_4	*0.756*	*0.736*	*0.713*	0.729	0.643	0.669	0.310	0.330	0.292	0.643	0.607	0.582	0.278	0.297	0.258	**0.733**	**0.651**	**0.674**
Q_5	*0.759*	*0.718*	*0.710*	0.714	0.666	0.649	0.381	0.399	0.353	0.637	0.610	0.580	0.377	0.393	0.345	**0.734**	**0.715**	**0.697**
Q_6	*0.874*	*0.841*	*0.833*	0.788	0.737	0.725	0.451	0.451	0.405	0.662	0.625	0.603	0.378	0.438	0.364	**0.795**	**0.756**	**0.742**
Q_1	*0.197*	*0.190*	*0.170*	**0.158**	**0.152**	**0.124**	0.013	0.018	0.013	0.146	0.147	0.120	0.034	0.019	0.018	0.114	0.100	0.089
Q_2	*0.191*	*0.216*	*0.173*	**0.170**	0.155	**0.136**	0.015	0.037	0.009	0.166	**0.167**	0.133	0.011	0.034	0.012	0.121	0.093	0.092
Q_3	*0.223*	*0.241*	*0.204*	0.201	**0.208**	0.173	0.006	0.021	0.007	**0.205**	0.204	**0.176**	0.019	0.029	0.019	0.118	0.112	0.102
Q_4	*0.176*	*0.189*	*0.156*	0.159	0.149	0.126	0.006	0.007	0.005	**0.174**	**0.173**	**0.144**	0.006	0.016	0.004	0.073	0.071	0.061
Q_5	*0.132*	*0.092*	*0.090*	**0.109**	0.080	**0.090**	0.013	0.017	0.008	0.104	**0.092**	0.085	0.004	0.087	0.006	0.089	0.075	0.070
Q_6	*0.211*	*0.224*	*0.192*	0.183	0.166	0.155	0.014	0.024	0.014	**0.186**	**0.185**	**0.157**	0.017	0.065	0.020	0.120	0.103	0.090

Table 11 (continued)

	LamBERTa			*TextCNN*			*BiLSTM*			*TextRCNN*			*Seq2Seq-A*			*Transformer*		
i	P	R	F^{μ}	P	R	F^{μ}	P	R	F^{μ}	P	R	F^{μ}	P	R	F^{μ}	P	R	F^{μ}
Q_1	*0.233*	*0.228*	*0.210*	0.147	0.137	0.123	0.009	0.009	0.008	**0.155**	**0.144**	**0.123**	0.001	0.005	0.002	0.102	0.089	0.086
Q_2	*0.316*	*0.292*	*0.274*	**0.186**	0.163	0.132	0.009	0.023	0.009	0.172	**0.169**	**0.143**	0.023	0.012	0.016	0.118	0.092	0.104
Q_3	*0.323*	*0.284*	*0.273*	**0.221**	**0.267**	**0.219**	0.006	0.013	0.008	0.178	0.173	0.151	0.010	0.019	0.012	0.193	0.115	0.124
Q_4	*0.299*	*0.259*	*0.250*	**0.216**	**0.187**	**0.170**	0.007	0.009	0.004	0.115	0.112	0.095	0.021	0.011	0.011	0.106	0.088	0.097
Q_5	*0.401*	*0.354*	*0.342*	0.271	**0.251**	0.222	0.016	0.016	0.009	**0.288**	0.232	**0.226**	0.005	0.020	0.006	0.186	0.144	0.152
Q_6	*0.445*	*0.392*	*0.372*	**0.357**	**0.322**	**0.294**	0.045	0.050	0.033	0.301	0.303	0.259	0.022	0.029	0.016	0.201	0.130	0.137



article id	C_1	C_2	C_3	C_4	SC_1	SC_2	SC_3	SC_4	SC_5	SC_6	SC_7	S_1	S_2	S_3	S_4	S_5	P_1	P_2
1	T	F	F	F	T	F	F	F	F	F	F	F	F	F	F	F	F	F
									…									
17	T	F	F	F	T	F	F	F	F	F	F	F	F	F	F	F	F	F
18	T	F	F	F	F	T	F	F	F	F	F	F	F	F	F	F	F	F
									…									
47	T	F	F	F	F	T	F	F	F	F	F	F	F	F	F	F	F	F
48	T	F	F	F	F	F	T	F	F	F	F	T	F	F	F	F	F	F
									…									
57	T	F	F	F	F	F	T	F	F	F	F	T	F	F	F	F	F	F
58	T	F	F	F	F	F	T	F	F	F	F	F	T	F	F	F	F	F
									…									
80	T	F	F	F	F	F	T	F	F	F	F	F	T	F	F	F	F	F
81	T	F	F	F	F	F	T	F	F	F	F	F	F	T	F	F	F	F
									…									
87	T	F	F	F	F	F	T	F	F	F	F	F	F	T	F	F	F	F
88	F	T	F	F	F	F	F	T	F	F	F	F	F	F	F	F	F	F
									…									

Fig. 6 Attribute-aware article prediction: Example book hierarchical organization (on the left) and excerpt of its corresponding attribute-aware article representation (on the right)

others. In fact, for such types of queries, the lack of masked language modeling in *Transformer* seems not to be compensated by the attention mechanism as it happens for the QType-1 and QType-2 queries. Moreover, the RNN models achieve lower scores than CNN-based or more advanced models, on all query sets. This indicates that the ability of *BiLSTM* and *Seq2Seq-A* of handling more distant token information (i.e., long range semantic dependency) and achieving complete abstraction at their bottom layers (without requiring multiple layer stacking like for CNNs) appear to vanish without a deep pre-training. In addition, CNN models are effective in extracting local and position-invariant features, and it has indeed been shown (e.g., Yin et al. 2017) that CNNs can successfully learn to classify a sentence (like QType-4 comment queries) or a paragraph (like QType-5 case law queries).

Our major finding is that, when comparing to the results obtained by LamBERTa models (cf. first column of Table 11), the best among the above competing methods turn out to be outperformed by the corresponding LamBERTa models, on all types of query. This confirms our initial expectation on the superiority of LamBERTa in learning classification models from few labeled examples per-class under a tough multi-class classification scenario, having a very large (i.e., in the order of hundreds) number of classes.

8.3.2 Attribute-aware law article prediction

As discussed in Sect. 2, the method in Hu et al. (2018) was conceived for attribute-aware charge prediction, and was evaluated on collected criminal cases using two types of text data: the fact of each case and the charges extracted from the penalty results of each case. Moreover, a number of attributes were defined as to distinguish the confusing charge pairs previously selected from the confusion matrix obtained by a charge prediction model.

Table 12 Attribute-aware article prediction: The *A-FewShotAP* model (Hu et al. 2018) trained with each ICC book annotated with the `UniRR.T`$^+$ labeling scheme, and tested over all sets of paraphrased-sentence-queries (QType-2, upper subtable), comment-sentence-queries (QType-4, second upper subtable), and case-queries (QType-5, bottom subtable). The table shows best-performing values of precision, recall, and macro-averaged F-measure. (LamBERTa performance values, formatted in italic, are also reported from Table 4 to ease the comparison with the competing method)

	LamBERTa			*A-FewShotAP* (Hu et al. 2018)		
i	P	R	F^M	P	R	F^M
Q_1	*0.866*	*0.841*	*0.853*	0.355	0.410	0.381
Q_2	*0.856*	*0.828*	*0.841*	0.328	0.378	0.351
Q_3	*0.886*	*0.861*	*0.873*	0.450	0.514	0.480
Q_4	*0.756*	*0.736*	*0.746*	0.319	0.384	0.348
Q_5	*0.759*	*0.718*	*0.738*	0.382	0.444	0.411
Q_6	*0.874*	*0.841*	*0.857*	0.412	0.474	0.441
Q_1	*0.197*	*0.190*	*0.194*	0.018	0.031	0.023
Q_2	*0.191*	*0.216*	*0.203*	0.023	0.043	0.030
Q_3	*0.223*	*0.241*	*0.231*	0.027	0.038	0.032
Q_4	*0.176*	*0.189*	*0.182*	0.029	0.047	0.036
Q_5	*0.132*	*0.092*	*0.108*	0.035	0.042	0.038
Q_6	*0.211*	*0.224*	*0.218*	0.031	0.037	0.034
Q_1	*0.233*	*0.228*	*0.230*	0.006	0.013	0.009
Q_2	*0.316*	*0.292*	*0.303*	0.016	0.021	0.018
Q_3	*0.323*	*0.284*	*0.302*	0.016	0.018	0.017
Q_4	*0.299*	*0.259*	*0.278*	0.007	0.010	0.008
Q_5	*0.401*	*0.354*	*0.376*	0.018	0.027	0.022
Q_6	*0.445*	*0.392*	*0.417*	0.025	0.037	0.030

To apply the above method to the ICC law article prediction task, we define an *attribute-aware representation* of the ICC article data by exploiting the available ICC hierarchical labeling of the articles of each book (cf. Sect. 3). Our objective is to leverage the ICC-classification based attributes as explicit knowledge about how to distinguish related groups of articles within the same book.

To this purpose, we adopt the following methodology. From the tree modeling the hierarchical organization into chapters, subchapters, sections and paragraphs of any given book, we treat each node as a boolean attribute and a complete path (from the chapter level to a leaf node) as an attribute-set assignment for each of the articles under that subtree path. We illustrate our defined procedure in Fig. 6, where for the sake of simplicity, the example shows a hypothetical book containing 228 articles and organized into four chapters (i.e., $C_1, \dots, C_4$), seven subchapters (i.e., $SC_1, \dots, SC_7$), five sections (i.e., $S_1, \dots, S_5$), and two paragraphs (i.e., P_1, P_2). Thus, eighteen attributes are defined in total, and each article in the book is associated with a binary vector (i.e., 1 means that an attribute is representative for the article, 0 otherwise); note also that the bunch of articles within the same hierarchical level subdivision share the attribute representation.

The ICC-heading attributes resulting from the application of the above procedure on each of the ICC books are reported in Appendix, Tables 14, 15, 16, 17, 18 and 19.

Experimental settings and results. We resorted to the software implementation of the method in Hu et al. (2018) provided by the authors[15] and made minimal adaptations to the code so to enable the method to work with our ICC data. We hereinafter refer to this method as *attribute-aware few-shot article prediction* model, *A-FewShotAP*.

Analogously to the previous stage of comparative evaluation, we conducted an extensive parameter-tuning phase of *A-FewShotAP*, by considering both default values and variations for the main parameters, such as number of layers, learning rate, number of epochs, batch size. Moreover, like for the other competitors, we used Italian Wikipedia pre-trained embeddings.

Table 12 summarizes the best-performing results obtained by *A-FewShotAP* over different types of query sets, namely paraphrased-sentence-queries, comment-sentence-queries, and case-queries.

As it can be observed, *A-FewShotAP* performance scores reveal to be never comparable to those produced by our LamBERTa models. Indeed, despite no information on article attributes is exploited in LamBERTa models, the latter achieve a large effectiveness gain over *A-FewShotAP*, regardless of the type of query.

Nonetheless, it is also worth noticing the beneficial effect of the attribute-aware article prediction when comparing *A-FewShotAP* with other RNN-based competing methods, particularly *BiLSTM* and *Seq2Seq-A*. Notably, although *A-FewShotAP* builds on a conventional LSTM—unlike *BiLSTM* and *Seq2Seq-A*, which utilize a bidirectional LSTM—it can achieve comparable or even higher performance than the other two methods (cf. Table 11): in fact, on QType-4 queries, *A-FewShotAP* behaves better than *BiLSTM* and (especially in terms of precision) than *Seq2Seq-A*, while it performs better than *Seq2Seq-A* and is generally as good as *BiLSTM* on QType-2 and QType-5 queries.

9 Conclusions

We presented LamBERTa, a novel BERT-based language understanding framework for law article retrieval as a prediction task. One key aspect of LamBERTa is that it is designed to deal with a challenging learning scenario, where the multi-class classification setting is characterized by hundreds of classes and very few, per-class training instances that are generated in an unsupervised fashion.

The purpose of our research is to show that a deep-learning-based civil-law article retrieval method can be helpful not only to legal experts to reduce their workload, but also to citizens who can benefit from such a system to save their search and consultation needs. Note also that, while focusing on the Italian Civil Code in its current version, the LamBERTa architecture can easily be generalized to learn from other law code systems.

We are currently working on an important extension of LamBERTa to enhance its capability of understanding patterns between different parts from a collection of

[15] https://github.com/thunlp/attribute_charge

law corpora (as it's the case of the books within the ICC), but also to enable LamBERTa to learn from external, heterogeneous legal sources, particularly to embed comments on the code and judicial decisions, also for entailment tasks. We believe this next step will contribute to the development of powerful tools that can model both sides of the same coin in predictive justice, so to deliver unprecedented solutions to different problems in artificial intelligence for law.

The ICC corpus and evaluation data are made available to the research community at https://people.dimes.unical.it/andreatagarelli/ai4law/.

Appendix

Table 13 compares article-driven multi-label performance results based on clusters of articles modeled either through TF-IDF vectors or LamBERTa embeddings. Note that, to ease the comparison, the results under the 'TF-IDF vectors' columns correspond to the performance of local models reported in Table 5.

Tables 14, 15, 16, 17, 18 and 19 list the ICC-heading attributes, for each of the ICC books, which were used in the task of attribute-aware law prediction.

Table 13 Article-driven, Clustering-based multi-label evaluation: comparison of results obtained by local models, with labeling scheme UniRR.T$^+$, based on clusters over TF-IDF representation vs. clusters over LamBERTa embeddings of the ICC articles, for all sets of book-sentence-queries (QType-1), paraphrased-sentence-queries (QType-2), comment-queries (QType-3), comment-sentence-queries (QType-4), and case-queries (QType-5). (Bold values correspond to the best model for each query-set and evaluation criterion)

Query-set		R		P		F^{μ}		F^{M}	
	i	TF-IDF vectors	LamBERTa embeddings	TF-IDF	LamBERTa embeddings	TF-IDF vectors	LamBERTa embeddings	TF-IDF vectors	LamBERTa embeddings
QType-1	Q_1	0.615	**0.641**	0.617	**0.643**	0.615	**0.641**	0.616	**0.642**
	Q_2	0.674	**0.682**	0.684	**0.687**	0.676	**0.684**	0.679	**0.685**
	Q_3	0.623	**0.677**	0.626	**0.674**	0.624	**0.675**	0.625	**0.675**
	Q_4	0.331	**0.454**	0.326	**0.456**	0.324	**0.454**	0.328	**0.455**
	Q_5	0.631	**0.719**	0.633	**0.722**	0.628	**0.719**	0.632	**0.720**
	Q_6	0.711	**0.781**	0.720	**0.784**	0.710	**0.782**	0.715	**0.782**
QType-2	Q_1	0.557	**0.575**	0.559	**0.577**	0.557	**0.575**	0.558	**0.576**
	Q_2	0.595	**0.662**	0.604	**0.666**	0.598	**0.663**	0.599	**0.664**
	Q_3	0.563	**0.859**	0.566	**0.884**	0.563	**0.849**	0.564	**0.871**
	Q_4	0.172	**0.748**	0.213	**0.769**	0.186	**0.727**	0.190	**0.759**
	Q_5	0.522	**0.606**	0.526	**0.609**	0.522	**0.606**	0.524	**0.607**
	Q_6	0.624	**0.682**	0.628	**0.690**	0.625	**0.684**	0.626	**0.686**
QType-3	Q_1	0.312	**0.329**	0.315	**0.333**	0.312	**0.331**	0.313	**0.331**
	Q_2	0.296	**0.320**	0.300	**0.322**	0.297	**0.320**	0.298	**0.321**
	Q_3	0.332	**0.349**	0.337	**0.353**	0.333	**0.350**	0.334	**0.351**
	Q_4	0.234	**0.249**	0.241	**0.253**	0.236	**0.250**	0.237	**0.251**
	Q_5	0.209	**0.330**	0.214	**0.333**	0.209	**0.330**	0.211	**0.331**
	Q_6	0.361	**0.372**	0.365	**0.373**	0.361	**0.371**	0.363	**0.372**

Table 13 (continued)

Query-set		R		P		F^{μ}		F^{M}	
	i	TF-IDF vectors	LamBERTa embeddings	TF-IDF	LamBERTa embeddings	TF-IDF vectors	LamBERTa embeddings	TF-IDF vectors	LamBERTa embeddings
QType-4	Q_1	0.227	**0.230**	0.227	**0.234**	0.226	**0.231**	0.227	**0.232**
	Q_2	0.205	**0.222**	0.207	**0.223**	0.205	**0.223**	0.206	**0.223**
	Q_3	0.259	**0.265**	0.261	**0.268**	0.258	**0.265**	0.260	**0.266**
	Q_4	0.163	**0.171**	0.164	**0.175**	0.164	**0.172**	0.163	**0.173**
	Q_5	0.151	**0.180**	0.152	**0.183**	0.150	**0.180**	0.151	**0.181**
	Q_6	0.236	**0.246**	0.238	**0.250**	0.235	**0.247**	0.237	**0.248**
QType-5	Q_1	0.283	**0.290**	0.289	**0.294**	0.284	**0.292**	0.286	**0.292**
	Q_2	0.294	**0.300**	0.304	**0.311**	0.298	**0.305**	0.299	**0.274**
	Q_3	0.298	**0.393**	0.302	**0.391**	0.299	**0.392**	0.300	**0.392**
	Q_4	0.274	**0.282**	0.276	**0.285**	0.275	**0.282**	0.275	**0.283**
	Q_5	0.378	**0.407**	0.382	**0.411**	0.378	**0.408**	0.380	**0.409**
	Q_6	0.404	**0.454**	0.408	**0.456**	0.405	**0.454**	0.406	**0.455**

Table 14 Unique headings of book subdivisions originally provided in the ICC and used in the attribute-aware article prediction evaluation task

	Attributes	Attributes (translated in English)
Book-1	1: ‘persone fisiche’, 2: ‘persone giuridiche’, 3: ‘disposizioni generali’, 4: ‘associazioni e fondazioni’, 5: ‘associazioni non riconosciute e comitati’, 6: ‘domicilio e residenza’, 7: ‘assenza e dichiarazione di morte presunta’, 8: ‘assenza’, 9: ‘dichiarazione di morte presunta’, 10: ‘ragioni eventuali che competono alla persona di cui si ignora l’esistenza o di cui è stata dichiarata la morte presunta’, 11: ‘parentela e affinità’, 12: ‘matrimonio’, 13: ‘promessa di matrimonio’, 14: ‘matrimonio celebrato davanti a ministri del culto cattolico e matrimonio celebrato davanti a ministri dei culti ammessi nello stato’, 15: ‘matrimonio celebrato davanti all’ufficiale dello stato civile’, 16: ‘condizioni necessarie per contrarre matrimonio’, 17: ‘formalità preliminari del matrimonio’, 18: ‘opposizioni al matrimonio’, 19: ‘celebrazione del matrimonio’, 20: ‘matrimonio dei cittadini in paese straniero e degli stranieri nel regno’, 21: ‘nullità del matrimonio’, 22: ‘prove della celebrazione del matrimonio’, 23: ‘disposizioni penali’, 24: ‘diritti e doveri che nascono dal matrimonio’, 25: ‘scioglimento del matrimonio e separazione dei coniugi’, 26: ‘regime patrimoniale della famiglia’, 27: ‘fondo patrimoniale’, 28: ‘comunione legale’, 29: ‘comunione convenzionale’, 30: ‘regime di separazione dei beni’, 31: ‘impresa familiare’, 32: ‘stato di figlio’, 33: ‘presunzione di paternità’, 34: ‘prove della filiazione’, 35: ‘azione di disconoscimento e azioni di contestazione e di reclamo dello stato di figlio’, 36: ‘riconoscimento dei figli nati fuori dal matrimonio’, 37: ‘dichiarazione giudiziale della paternità e della maternità’, 38: ‘legittimazione dei figli naturali’, 39: ‘adozione di persone maggiori di età’, 40: ‘adozione di persone maggiori di età e suoi effetti’, 41: ‘forme dell’adozione di persone di maggiore età’, 42: ‘responsabilità genitoriale e diritti e doveri del figlio’, 43: ‘diritti e doveri del figlio’, 44: ‘esercizio della responsabilità genitoriale a seguito di separazione, scioglimento, cessazione degli effetti civili, annullamento, nullità del matrimonio ovvero all’esito di procedimenti relativi ai figli nati fuori del matrimonio’, 45: ‘ordini di protezione contro gli abusi familiari’, 46: ‘tutela e emancipazione’, 47: ‘tutela dei minori’, 48: ‘giudice tutelare’, 49: ‘tutore e protutore’, 50: ‘esercizio della tutela’, 51: ‘cessazione del tutore dall’ufficio’, 52: ‘rendimento del conto finale’, 53: ‘emancipazione’, 54: ‘affiliazione e affidamento’, 55: ‘misure di protezione delle persone prive in tutto od in parte di autonomia’, 56: ‘amministrazione di sostegno’, 57: ‘interdizione, inabilitazione e incapacità naturale’, 58: ‘alimenti’, 59: ‘atti dello stato civile’	1: ‘natural persons’, 2: ‘legal persons’, 3: ‘general provisions’, 4: ‘associations and foundations’, 5: ‘unrecognized associations and committees’, 6: ‘domicile and residence’, 7: ‘absence and declaration of presumed death’, 8: ‘absence’, 9: ‘declaration of presumed death’, 10: ‘possible reasons for the person whose existence is unknown or whose existence has been declared presumed death’, 11: ‘kinship and affinity’, 12: ‘marriage’, 13: ‘promise of marriage’, 14: ‘marriage celebrated before Catholic ministers and marriage celebrated before ministers of worship admitted in the state’, 15: ‘marriage celebrated before the registrar’, 16: ‘necessary conditions for marriage’, 17: ‘preliminary formalities for marriage’, 18: ‘opposition to marriage’, 19: ‘celebration of marriage’, 20: ‘marriage of citizens in a foreign country and foreigners in the kingdom’, 21: ‘nullity of marriage’, 22: ‘proof of celebration of marriage’, 23: ‘penal provisions’, 24: ‘rights and duties arising from marriage’, 25: ‘dissolution of marriage and separation of spouses’, 26: ‘family property regime’, 27: ‘patrimonial fund’, 28: ‘legal community’, 29: ‘conventional community’, 30: ‘property separation regime’, 31: ‘family business’, 32: ‘child status’, 33: ‘presumption of paternity’, 34: ‘evidence of filiation’, 35: ‘action of denial and actions of contestation and complaint of the child status’, 36: ‘recognition of children born out of wedlock’, 37: ‘judicial declaration of paternity and maternity’, 38: ‘legitimation of natural children’, 39: ‘adoption of older people’, 40: ‘adoption of older people and its effects’, 41: ‘forms of adoption of older people’, 42: ‘parental responsibility and rights and duties of the child’, 43: ‘rights and duties of the child’, 44: ‘practice of parental responsibility following separation, dissolution, termination of civil effects, annulment, nullity of marriage or the outcome of proceedings relating to children born out of wedlock’, 45: ‘protection orders against family abuse’, 46: ‘guardianship and emancipation’, 47: ‘guardianship of minors’, 48: ‘tutelary judge’, 49: ‘guardian and protutore’, 50: ‘practice of guardianship’, 51: ‘termination of the guardian from office’, 52: ‘return of the final account’, 53: ‘emancipation’, 54: ‘affiliation and custody’, 55: ‘protection measures for persons lacking in whole or in part autonomy’, 56: ‘support administration’, 57: ‘disqualification, disability and natural incapacity’, 58: ‘alimony’, 59: ‘civil status documents’

Table 15 *(cont.)* Unique headings of book subdivisions originally provided in the ICC and used in the attribute-aware article prediction evaluation task

	Attributes	Attributes (translated in English)
Book-2	1: ‘disposizioni generali sulle successioni’, 2: ’apertura della successione, delazione e acquisto dell’eredità’, 3: ‘capacità di succedere’, 4: ‘indegnità’, 5: ‘rappresentazione’, 6: ‘accettazione dell’eredità’, 7: ‘disposizioni generali’, 8: ‘beneficio d’inventario’, 9: ‘separazione dei beni del defunto da quelli dell’erede’, 10: ‘rinunzia all’eredità’, 11: ‘eredità giacente’, 12: ‘petizione di eredità’, 13: ‘legittimari’, 14: ‘diritti riservati ai legittimari’, 15: ‘reintegrazione della quota riservata ai legittimari’, 16: ‘successioni legittime’, 17: ‘successione dei parenti’, 18: ‘successione del coniuge’, 19: ‘successione dello stato’, 20: ‘successioni testamentarie’, 21: ‘capacità di disporre per testamento’, 22: ‘capacità di ricevere per testamento’, 23: ‘forma dei testamenti’, 24: ‘testamenti ordinari’, 25: ‘testamenti speciali’, 26: ‘pubblicazione dei testamenti olografi e testamenti segreti’, 27: ‘istituzione di erede e legati’, 28: ‘disposizioni condizionali, a termine e modali’, 29: ‘legati’, 30: ‘diritto di accrescimento’, 31: ‘revocazione delle disposizioni testamentarie’, 32: ‘sostituzioni’, 33: ‘sostituzione ordinaria’, 34: ‘sostituzione fedecommissaria’, 35: ‘esecutori testamentari’, 36: ‘divisione’, 37: ‘collazione’, 38: ‘pagamento dei debiti’, 39: ‘effetti della divisione e garanzia delle quote’, 40: ‘annullamento e rescissione in materia di divisione’, 41: ‘patto di famiglia’, 42: ‘donazioni’, 43: ‘capacità di disporre e di ricevere per donazione’, 44: ‘forma e effetti della donazione’, 45: ‘revocazione delle donazioni’	1: ‘general provisions on succession’, 2: ‘opening of succession, delation and acquisition of inheritance’, 3: ‘ability to succeed’, 4: ‘unworthiness’, 5: ‘representation’, 6: ‘acceptance of the inheritance’, 7: ‘general provisions’, 8: ‘inventory benefit’, 9: ‘separation of the deceased’s assets from those of the heir’, 10: ‘disclaim of inheritance’, 11: ‘lying inheritance’, 12: ‘petition of inheritance’, 13: ‘heirs’, 14: ‘rights reserved for the heirs’, 15: ‘reinstatement of the quota reserved for the heirs’, 16: ‘legitimate succession’, 17: ‘succession of relatives’, 18: ‘succession of spouse’, 19: ‘succession of the state’, 20: ‘testamentary successions’, 21: ‘ability to dispose by testament’, 22: ‘ability to receive by testamemt’, 23: ‘form of testaments’, 24: ‘ordinary testaments ’, 25: ‘special testaments’, 26: ‘publication of holographic testaments and secret testaments’, 27: ‘establishment of heirs and legacies’, 28: ‘conditional provisions, forward and modal’, 29: ‘legacies’, 30: ‘right of accretion’, 31: ‘revocation of testamentary dispositions’, 32:‘substitutions’, 33: ‘ordinary substitutions’, 34: ‘fidecommissary substitutions’, 35: ‘testamentary executors’, 36: ‘division’, 37: ‘collation’, 38: ‘payment of debts’, 39: ‘effects of division andguarantee of quotas’, 40: ‘annulment and rescission of division’, 41: ‘family pact’, 42: ‘donations’, 43: ‘ability to dispose and receive by donation’, 44: ‘forms and effects of donation’, 45: ‘revocation of donations’

Table 16 *(cont.)* Unique headings of book subdivisions originally provided in the ICC and used in the attribute-aware article prediction evaluation task

	Attributes	Attributes (translated in English)
Book-3	1: ‘beni’, 2: ‘beni in generale’, 3: ‘beni nell’ordine corporativo’, 4: ‘beni immobili e mobili’, 5: ‘frutti’, 6: ‘beni appartenenti allo stato, agli enti pubblici e agli enti ecclesiastici’, 7: ‘proprietà’, 8: ‘disposizioni generali’, 9: ‘proprietà fondiaria’, 10: ‘riordinamento della proprietà rurale’, 11: ‘bonifica integrale’, 12: ‘vincoli idrogeologici e difese fluviali’, 13: ‘proprietà edilizia’, 14: ‘distanze nelle costruzioni, piantagioni e scavi, e muri, fossi e siepi interposti tra i fondi’, 15: ‘luci e vedute’, 16: ‘stillicidio’, 17: ‘acque’, 18: ‘modi di acquisto della proprietà’, 19: ‘occupazione e invenzione’, 20: ‘accessione, specificazione, unione e commistione’, 21: ‘azioni a difesa della proprietà’, 22: ‘superficie’, 23: ‘enfiteusi’, 24: ‘usufrutto, uso e abitazione’, 25: ‘usufrutto’, 26: ‘diritti nascenti dall’usufrutto’, 27: ‘obblighi nascenti dall’usufrutto’, 28: ‘estinzione e modificazioni dell’usufrutto’, 29: ‘uso e abitazione’, 30: ‘servitù prediali’, 31: ‘servitù coattive’, 32: ‘acquedotto e scarico coattivo’, 33: ‘appoggio e infissione di chiusa’, 34: ‘somministrazione coattiva di acqua a un edificio o a un fondo’, 35: ‘passaggio coattivo’, 36: ‘elettrodotto coattivo e passaggio coattivo di linee teleferiche’, 37: ‘servitù volontarie’, 38: ‘servitù acquistate per usucapione e per destinazione del padre di famiglia’, 39: ‘esercizio delle servitù’, 40: ‘estinzione delle servitù’, 41: ‘azioni a difesa delle servitù’, 42: ‘alcune servitù in materia di acque’, 43: ‘servitù di presa o di derivazione di acqua’, 44: ‘servitù degli scoli e degli avanzi di acqua’, 45: ‘comunione’, 46: ‘comunione in generale’, 47: ‘condominio negli edifici’, 48: ‘possesso’, 49: ‘effetti del possesso’, 50: ‘diritti e obblighi del possessore nella restituzione della cosa’, 51: ‘possesso di buona fede di beni mobili’, 52: ‘usucapione’, 53: ‘azioni a difesa del possesso’, 54: ‘denunzia di nuova opera e di danno temuto’	1: ‘assets’, 2: ‘assets in general’, 3: ‘assets in the corporate order’, 4: ‘immovable and movable assets’, 5: ‘civil fruits’, 6: ‘assets belonging to the state, to public authorities and to ecclesiastical authorities’, 7: ‘property’, 8: ‘general provisions’, 9: ‘landed property’, 10: ‘rearrangement of rural property’, 11: ‘integral reclamation’, 12: ‘hydrogeological constraints and river defenses’, 13: ‘building property’, 14: ‘distances in buildings, plantations and excavations, and walls, ditches and hedges interposed between the bottoms’, 15: ‘lights and views’, 16: ‘dripping’, 17: ‘waters’, 18: ‘ways of purchasing property’, 19 : ‘occupation and invention’, 20: ‘accession, specification, union and admixture’, 21: ‘actions in defense of property’, 22: ‘surface’, 23: ‘emphyteusis’, 24: ‘usufruct, use and dwelling’, 25: ‘usufruct’, 26: ‘rights arising from usufruct’, 27: ‘obligations arising from usufruct’, 28: ‘extinction and modifications of usufruct’, 29: ‘use and dwelling’, 30: ‘predial servitude’, 31: ‘coercive servitude’, 32: ‘aqueduct and coercive drainage’, 33: ‘support and lock driving’, 34: ‘coercive administration of water to a building or ground’, 35: ‘coercive passage’, 36: ‘coercive power line and coercive passage of cableways’, 37: ‘voluntary servitude’, 38: ‘servitude purchased for usucapion and for the use of the father of a family’, 39: ‘practice of the servitude’, 40: ‘extinction of the servitude’, 41:’ actions in defense of the servitude’, 42: ‘some servitude concerning water’, 43: ‘servitude of water intake or diversion’, 44: ‘servitude of drains and leftovers of water’, 45: ‘ communion’, 46: ‘communion in general’, 47: ‘condominium in buildings’, 48: ‘possession’, 49: ’effects of possession’, 50: ‘rights and obligations of the owner to return the property’, 51: ‘possession of movable property in good faith’, 52: ‘usucaption’, 53: ‘actions in defense of possession’, 54: ‘denunciation of new work and feared damage’

Table 17 *(cont.)* Unique headings of book subdivisions originally provided in the ICC and used in the attribute-aware article prediction evaluation task

	Attributes	Attributes (translated in English)
Book-4	1: ‘obbligazioni in generale’, 2: ‘disposizioni preliminari’, 3: ‘adempimento delle obbligazioni’, 4: ‘adempimento in generale’, 5: ‘pagamento con surrogazione’, 6: ‘mora del creditore’, 7: ‘inadempimento delle obbligazioni’, 8: ‘modi di estinzione delle obbligazioni diversi dall’adempimento’, 9: ‘novazione’, 10: ‘remissione’, 11: ‘compensazione’, 12: ‘confusione’, 13: ‘impossibilità sopravvenuta per causa non imputabile al debitore’, 14: ‘cessione dei crediti’, 15: ‘delegazione, espromissione e accollo’, 16: ‘alcune specie di obbligazioni’, 17: ‘obbligazioni pecuniarie’, 18: ‘obbligazioni alternative’, 19: ‘obbligazioni in solido’, 20: ‘obbligazioni divisibili e indivisibili’, 21: ‘contratti in generale’, 22: ‘requisiti del contratto’, 23: ‘accordo delle parti’, 24: ‘causa del contratto’, 25: ‘oggetto del contratto’, 26: ‘forma del contratto’, 27: ‘condizione nel contratto’, 28: ‘interpretazione del contratto’, 29: ‘effetti del contratto’, 30: ‘disposizioni generali’, 31: ‘clausola penale e caparra’, 32: ‘rappresentanza’, 33: ‘contratto per persona da nominare’, 34: ‘cessione del contratto’, 35: ‘contratto a favore di terzi’, 36: ‘simulazione’, 37: ‘nullità del contratto’, 38: ‘annullabilità del contratto’, 39: ‘incapacità’, 40: ‘vizi del consenso’, 41: ‘azione di annullamento’, 42: ‘rescissione del contratto’, 43: ‘risoluzione del contratto’, 44: ‘risoluzione per inadempimento’, 45: ‘impossibilità sopravvenuta’, 46: ‘eccessiva onerosità’, 47: ‘contratti del consumatore’, 48: ‘singoli contratti’, 49: ‘vendita’, 50: ‘obbligazioni del venditore’, 51: ‘obbligazioni del compratore’, 52: ‘riscatto convenzionale’, 53: ‘vendita di cose mobili’, 54: ‘vendita dei beni di consumo’, 55: ‘vendita con riserva di gradimento, a prova, a campione’, 56: ‘vendita con riserva della proprietà’, 57: ‘vendita su documenti e con pagamento contro documenti’, 58: ‘vendita a termine di titoli di credito’, 59: ‘vendita di cose immobili’, 60: ‘vendita di eredità’, 61: ‘riporto’, 62: ‘permuta’, 63: ‘contratto estimatorio’, 64: ‘somministrazione’, 65: ‘locazione’, 66: ‘locazione di fondi urbani’, 67: ‘affitto’, 68: ‘affitto di fondi rustici’, 69: ‘affitto a coltivatore diretto’, 70: ‘appalto’, 71: ‘trasporto’, 72: ‘trasporto di persone’, 73: ‘trasporto di cose’, 74: ‘mandato’, 75: ‘obbligazioni del mandatario’, 76: ‘obbligazioni del mandante’, 77: ‘estinzione del mandato’, 78: ‘commissione’, 79: ‘spedizione’, 80: ‘contratto di agenzia’, 81: ‘mediazione’, 82: ‘deposito’, 83: ‘deposito in generale’, 84: ‘deposito in albergo’, 85: ‘deposito nei magazzini generali’, 86: ‘sequestro convenzionale’, 87: ‘comodato’, 88: ‘mutuo’, 89: ‘conto corrente’, 90: ‘contratti bancari’, 91: ‘depositi bancari’, 92: ‘servizio bancario delle cassette di sicurezza’, 93: ‘apertura di credito bancario’, 94: ‘anticipazione bancaria’, 95: ‘operazioni bancarie in conto corrente’, 96: ‘sconto bancario’, 97: ‘rendita perpetua’, 98: ‘rendita vitalizia’, 99: ‘assicurazione’, 100: ‘assicurazione contro i danni’, 101: ‘assicurazione sulla vita’, 102: ‘riassicurazione’, 103: ‘disposizioni finali’, 104: ‘giuoco e scommessa’, 105: ‘fideiussione’, 106: ‘rapporti tra creditore e fideiussore’, 107: ‘rapporti tra fideiussore e debitore principale’, 108: ‘rapporti tra più fideiussori’, 109: ‘estinzione della fideiussione’, 110: ‘mandato di credito’, 111: ‘anticresi’, 112: ‘transazione’, 113: ‘cessione dei beni ai creditori’, 114: ‘promesse unilaterali’, 115: ‘titoli di credito’, 116: ‘titoli al portatore’, 117: ‘titoli all’ordine’, 118: ‘titoli nominativi’, 119: ‘gestione di affari’, 120: ‘pagamento dell’indebito’, 121: ‘arricchimento senza causa’, 122: ‘fatti illeciti’	1: ‘obligations in general’, 2: ‘preliminary provisions’, 3: ‘fulfillment of obligations’, 4: ‘fulfillment in general’, 5: ‘payment with subrogation’, 6: ‘default of creditor’, 7: ‘default of obligations’, 8: ‘ways of extinguishing obligations other than performance’, 9: ‘novation’, 10: ‘remission’, 11: ‘set-off’, 12: ‘confusion’, 13: ‘impossibility occurred for reasons not attributable to the debtor’, 14:‘assignment of credits’, 15: ‘delegation, expression and assumption’, 16: ‘some kinds of obligations’, 17: ‘pecuniary obligations’, 18: ‘alternative obligations’, 19: ‘joint and several obligations’, 20: ‘divisible and indivisible obligations’, 21: ‘contracts in general’, 22: ‘contract requirements’, 23: ‘agreement of the parties’, 24 : ‘cause of the contract’, 25: ‘object of the contract’, 26: ‘form of the contract’, 27: ‘condition in the contract’, 28: ‘interpretation of the contract’, 29: ‘effects of the contract’, 30: ‘general provisions’, 31: ‘penalty clause and deposit’, 32: ‘representation’, 33: ‘contract for person to be appointed’, 34: ‘transfer of the contract’, 35: ‘contract in favor of third parties’, 36: ‘simulation’, 37: ‘nullity of the contract’, 38: ‘voidability of the contract’, 39: ‘incapacity’, 40: ‘vices of consent’, 41: ‘action for annulment’ , 42: ‘termination of the contract’, 43: ‘resolution of the contract’, 44: ‘termination due to non-fulfillment’, 45: ‘occurred impossibility’, 46: ‘excessive onerousness’, 47: ‘consumer contracts’, 48: ‘individual contracts’, 49: ‘sale’, 50: ‘seller’s obligations’, 51: ‘buyer’s obligations’, 52: ‘conventional redemption’, 53: ‘sale of movable things’, 54: ‘sale of consumer goods’, 55: ‘sale subject to approval, trial, sample’, 56: ‘sale subject to ownership’, 57: ‘sale on documents and with payment against documents’, 58: ‘forward sale of debt securities’, 59: ‘sale of real estate’, 60: ‘sale of inheritance’, 61: ‘return’, 62: ‘exchange’, 63: ‘estimation contract’, 64: ‘administration’, 65: ‘lease’, 66: ‘lease of urban land’, 67: ’rent’, 68: ‘rent of rustic land’, 69: ‘rent to direct farmer’, 70: ’contract’, 71: ‘transport’, 72: ‘transport of people’, 73: ‘transport of things’, 74: ‘warrant’, 75: ‘agent’s obligations’, 76: ’principal’s obligations’, 77: ‘termination of the warrant’, 78: ’commission’, 79: ‘shipment’, 80: ‘agency contract’, 81: ’mediation’, 82: ‘deposit’, 83: ‘deposit in general’, 84: ‘deposit in hotel’, 85: ‘deposit in general warehouses’, 86: ‘conventional confiscation’, 87: ‘free loan’, 88: ‘mortgage’, 89: ‘checking account’, 90: ‘bank contracts’, 91: ‘bank deposits’, 92: ‘safe deposit box banking service’, 93: ‘bank credit opening’, 94: ‘bank advance’, 95: ‘checking account banking’, 96: ‘bank discount’, 97: ‘perpetual income’, 98: ‘life annuity’, 99: ‘insurance’, 100: ‘damage insurance’, 101: ‘life insurance’, 102: ‘reinsurance’, 103: ‘final provisions’, 104: ‘game and bet’, 105: ‘surety’, 106: ‘relationship between creditor and guarantor’, 107: ‘relationship between guarantor and principal debtor’, 108: ‘relationship between several guarantors’, 109: ‘termination of surety’, 110: ‘credit warrant’, 111: ‘anticresi’, 112: ‘transaction’, 113: ‘transfer of assets to creditors’, 114: ‘unilateral promises’, 115: ‘debt securities’, 116: ‘bearer securities’, 117: ‘order securities’, 118: ‘registered securities’, 119: ‘business management’, 120: ‘undue payment’, 121: ‘causeless enrichment’, 122: ‘illegal deeds’

Table 18 *(cont.)* Unique headings of book subdivisions originally provided in the ICC and used in the attribute-aware article prediction evaluation task

	Attributes	Attributes (translated in English)
Book-5	1: ‘disciplina delle attività professionali’, 2: ‘disposizioni generali’, 3: ‘ordinanze corporative e accordi economici collettivi’, 4: ‘contratto collettivo di lavoro e norme equiparate’, 5: ‘lavoro nell’impresa’, 6: ‘impresa in generale’, 7: ‘imprenditore’, 8: ‘collaboratori dell’imprenditore’, 9: ‘rapporto di lavoro’, 10: ‘costituzione del rapporto di lavoro’, 11: ‘diritti e obblighi delle parti’, 12: ‘previdenza e assistenza’, 13: ‘estinzione del rapporto di lavoro’, 14: ‘disposizioni finali’, 15: ‘tirocinio’, 16: ‘impresa agricola’, 17: ‘mezzadria’, 18: ‘colonia parziaria’, 19: ‘soccida’, 20: ‘soccida semplice’, 21: ‘soccida parziaria’, 22: ‘soccida con conferimento di pascolo’, 23: ‘disposizione finale’, 24: ‘imprese commerciali e altre imprese soggette a registrazione’, 25: ‘registro delle imprese’, 26: ‘obbligo di registrazione’, 27: ‘disposizioni particolari per le imprese commerciali’, 28: ‘rappresentanza’, 29: ‘scritture contabili’, 30: ‘insolvenza’, 31: ‘lavoro autonomo’, 32: ‘professioni intellettuali’, 33: ‘lavoro subordinato in particolari rapporti’, 34: ‘lavoro domestico’, 35: ‘società’, 36: ‘società semplice’, 37: ‘rapporti tra i soci’, 38: ‘rapporti con i terzi’, 39: ‘scioglimento della società’, 40: ‘scioglimento del rapporto sociale limitatamente a un socio’, 41: ‘società in nome collettivo’, 42: ‘società in accomandita semplice’, 43: ‘società per azioni’, 44: ‘costituzione per pubblica sottoscrizione’, 45: ‘promotori e soci fondatori’, 46: ‘patti parasociali’, 47: ‘conferimenti’, 48: ‘azioni e altri strumenti finanziari partecipativi’, 49: ‘assemblea’, 50: ‘amministrazione e controllo’, 51: ‘amministratori’, 52: ‘collegio sindacale’, 53: ‘revisione legale dei conti’, 54: ‘sistema dualistico’, 55: ‘sistema monistico’, 56: ‘obbligazioni’, 57: ‘libri sociali’, 58: ‘bilancio’, 59: ‘modificazioni dello statuto’, 60: ‘patrimoni destinati ad uno specifico affare’, 61: ‘società con partecipazione dello stato o di enti pubblici’, 62: ‘società di interesse nazionale’, 63: ‘società in accomandita per azioni’, 64: ‘società a responsabilità limitata’, 65: ‘conferimenti e quote’, 66: ‘amministrazione della società e controlli’, 67: ‘decisioni dei soci’, 68: ‘modificazioni dell’atto costitutivo’, 69: ‘scioglimento e liquidazione delle società di capitali’, 70: ‘direzione e coordinamento di società’, 71: ‘trasformazione, fusione e scissione’, 72: ‘trasformazione’, 73: ‘fusione delle società’, 74: ‘scissione delle società’, 75: ‘società costituite all’estero’, 76: ‘società cooperative e mutue assicuratrici’, 77: ‘società cooperative’, 78: ‘disposizioni generali di società cooperative a mutualità prevalente’, 79: ‘costituzione’, 80: ‘quote e azioni’, 81: ‘organi sociali’, 82: ‘controlli’, 83: ‘mutue assicuratrici’, 84: ‘associazione in partecipazione’, 85: ‘azienda’, 86: ‘ditta e insegna’, 87: ‘marchio’, 88: ‘diritti sulle opere dell’ingegno e sulle invenzioni industriali’, 89: ‘diritto di autore sulle opere dell’ingegno letterarie e artistiche’, 90: ‘diritto di brevetto per invenzioni industriali’, 91: ‘diritto di brevetto per modelli di utilità e di registrazione per disegni e modelli’, 92: ‘disciplina della concorrenza e dei consorzi’, 93: ‘disciplina della concorrenza’, 94: ‘concorrenza sleale’, 95: ‘consorzi per il coordinamento della produzione e degli scambi’, 96: ‘consorzi con attività esterna’, 97: ‘consorzi obbligatori’, 98: ‘controlli dell’autorità governativa’, 99: ‘disposizioni penali in materia di società, di consorzi e di altri enti privati’, 100: ‘falsità’, 101: ‘illeciti commessi dagli amministratori’, 102: ‘illeciti commessi mediante omissione’, 103: ‘altri illeciti, circostanze attenuanti e misure di sicurezza patrimoniali’	1: ‘regulation of professional activities’, 2: ‘general provisions’, 3: ‘corporate regulations and collective economic agreements’, 4: ‘collective bargaining agreement and equivalent rules’, 5: ‘work in enterprise’, 6: ‘enterprise in general’, 7: ‘entrepreneur’, 8: ‘collaborators of the entrepreneur’, 9: ‘employment relationship’, 10: ‘establishment of the employment relationship’, 11: ‘rights and obligations of the parties’, 12: ‘social security and assistance’, 13: ‘termination of the employment relationship’, 14: ‘final provisions’, 15: ‘apprenticeship’, 16: ‘agricultural enterprise’, 17: ‘sharecropping’, 18: ‘partial colony’, 19: ‘soccida’, 20: ’simple soccida’, 21: ‘partial soccida’, 22: ‘soccida with granting of pasture’, 23: ‘final provision’, 24: ‘commercial enterprises and other enterprises subject to registration’, 25: ‘business register’, 26: ‘obligation of registration’, 27: ‘special provisions for commercial enterprises’, 28: ‘representation’, 29: ‘accounting records’, 30: ‘insolvency’, 31: ‘self-employment’, 32: ‘intellectual professions’, 33: ‘subordinate work in particular relationships’, 34: ‘domestic work’, 35: ‘company’, 36: ‘simple company’, 37: ‘relationships between shareholders’, 38: ‘relationships with third parties’, 39: ‘dissolution of the company’, 40: ‘dissolution of the social relationship limited to one shareholder’, 41: ‘collective denomination company’, 42: ‘limited partnership company’, 43: ‘joint stock company’, 44: ‘constitution by public subscription’, 45: ‘promoters and founding partners’, 46: ‘shareholders’ agreements’, 47: ‘contributions’, 48: ‘shares and other equity financial instruments’, 49: ‘shareholders’ meeting’, 50: ‘administration and control’, 51: ‘directors’, 52: ‘board of statutory auditors’, 53: ‘statutory audit’, 54: ‘two-tier system’, 55: ‘one-tier system’, 56: ‘bonds’, 57: ‘company books’, 58: ‘balance sheet’, 59: ’amendments to the statute’, 60: ‘assets intended for a specific business’, 61: ‘company with state participation or public authorities’, 62: ‘company of national interest’, 63: ‘company limited by shares’, 64: ‘company with limited responsibility’, 65: ‘contributions and shares’, 66: ‘company administration and controls’, 67: ‘shareholders’ decisions’, 68: ‘amendments to the articles of association’, 69: ‘dissolution and liquidation of corporations’, 70: ‘management and coordination of companies’, 71: ‘transformation, merger and spin-off’, 72: ‘transformation’, 73:’merger of companies’, 74: ‘spin-off of companies’, 75: ‘companies incorporated abroad’, 76: ‘cooperative companies and mutual insurance companies’, 77: ‘cooperative companies’, 78:’ general provisions of cooperative societies with prevalent mutuality’, 79: ‘incorporation’, 80: ‘quotas and shares’, 81: ‘corporate bodies’, 82: ‘controls’, 83: ‘mutual insurance companies’, 84: ‘association in participation’, 85: ‘firm’, 86: ‘firm and sign’, 87: ‘trademark’, 88: ‘intellectual property rights and industrial inventions’, 89: ‘copyright on literary and artistic intellectual works’, 90: ‘patent law for industrial inventions’, 91: ‘patent law for utility models and registration for designs and models’, 92: ‘competition and consortium regulations’, 93: ‘competition rules’, 94: ‘unfair competition’, 95: ‘consortia for the coordination of production and trade’, 96: ‘consortia with external activities’, 97: ‘compulsory consortia’, 98: ‘controls by the governmental authority’, 99: ‘criminal provisions concerning companies, consortia and other private authorities’, 100: ‘falsity’, 101: ‘offenses committed by administrators’, 102: ‘offenses committed by omission’, 103: ‘other offenses, mitigating circumstances and asset security measures’

Table 19 *(cont.)* Unique headings of book subdivisions originally provided in the ICC and used in the attribute-aware article prediction evaluation task

	Attributes	Attributes (translated in English)
Book-6	1: ‘trascrizione’, 2: ‘trascrizione degli atti relativi ai beni immobili’, 3: ‘pubblicità dei registri immobiliari e responsabilità dei conservatori’, 4: ‘trascrizione degli atti relativi ad alcuni beni mobili’, 5: ‘trascrizione relativamente alle navi, agli aeromobili e agli autoveicoli’, 6: ‘trascrizione relativamente ad altri beni mobili’, 7: ‘prove’, 8: ‘disposizioni generali’, 9: ‘prova documentale’, 10: ‘atto pubblico’, 11: ‘scrittura privata’, 12: ‘scritture contabili delle imprese soggette a registrazione’, 13: ‘riproduzioni meccaniche’, 14: ‘taglie o tacche di contrassegno’, 15: ‘copie degli atti’, 16: ‘atti di ricognizione o di rinnovazione’, 17: ‘prova testimoniale’, 18: ‘presunzioni’, 19: ‘confessione’, 20: ‘giuramento’, 21: ‘responsabilità patrimoniale, cause di prelazione e conservazione della garanzia patrimoniale’, 22: ‘privilegi’, 23: ‘privilegi sui mobili’, 24: ‘privilegi generali sui mobili’, 25: ‘privilegi sopra determinati mobili’, 26: ‘privilegi sopra gli immobili’, 27: ‘ordine dei privilegi’, 28: ‘pegno’, 29: ‘pegno dei beni mobili’, 30: ‘pegno di crediti e altri diritti’, 31: ‘ipoteche’, 32: ‘ipoteca legale’, 33: ‘ipoteca giudiziale’, 34: ‘ipoteca volontaria’, 35: ‘iscrizione e rinnovazione delle ipoteche’, 36: ‘iscrizione’, 37: ‘rinnovazione’, 38: ‘ordine delle ipoteche’, 39: ‘effetti dell’ipoteca rispetto al terzo acquirente’, 40: ‘effetti dell’ipoteca rispetto al terzo datore’, 41: ‘riduzione delle ipoteche’, 42: ‘estinzione delle ipoteche’, 43: ‘cancellazione dell’iscrizione’, 44: ‘modo di liberare i beni dalle ipoteche’, 45: ‘rinunzia e astensione del creditore nell’espropriazione forzata’, 46: ‘mezzi di conservazione della garanzia patrimoniale’, 47: ‘azione surrogatoria’, 48: ‘azione revocatoria’, 49: ‘sequestro conservativo’, 50: ‘tutela giurisdizionale dei diritti’, 51: ‘esecuzione forzata’, 52: ‘espropriazione’, 53: ‘effetti del pignoramento’, 54: ‘effetti della vendita forzata e dell’assegnazione’, 55: ‘espropriazione di beni oggetto di vincoli di indisponibilità o di alienazioni a titolo gratuito’, 56: ‘esecuzione forzata in forma specifica’, 57: ‘prescrizione e decadenza’, 58: ‘prescrizione’, 59: ‘sospensione della prescrizione’, 60: ‘interruzione della prescrizione’, 61: ‘termine della prescrizione’, 62: ‘prescrizione ordinaria’, 63: ‘prescrizioni brevi’, 64: ‘prescrizioni presuntive’, 65: ‘computo dei termini’, 66: ‘decadenza’	1: ‘transcription’, 2: ‘transcription of deeds relating to immovable properties’, 3: ‘advertising of real estate registers and liability of conservators’, 4: ‘transcription of deeds relating to some movable property’, 5: ‘transcription relating to ships, aircraft and motor vehicles’, 6: ‘transcription relating to other movable properties’, 7: ‘evidence’, 8: ‘general provisions’, 9: ‘documentary evidence’, 10: ‘public deed’, 11: ‘private deed’, 12: ‘accounting records of companies subject to registration’, 13: ‘mechanical reproductions’, 14: ‘sizes or mark notches’, 15: ‘copies of deeds’, 16: ‘acts of recognition or renewal’, 17: ‘witness evidence’, 18: ‘presumptions’, 19: ‘confession’, 20: ‘oath’, 21: ‘property liability, causes of preemption and retention of the patrimonial guarantee’, 22: ‘privileges’, 23: ‘privileges on movables’, 24: ‘general privileges on movables’, 25: ‘privileges over certain movables’, 26: ‘privileges over real estate’, 27: ‘order of privileges’, 28: ’pledge’, 29: ‘pledge of movable property’, 30: ‘pledge of credits and other rights’, 31: ‘mortgages’, 32: ‘legal mortgage’, 33: ’judicial mortgage’, 34: ‘voluntary mortgage’, 35: ‘registration and renewal of mortgages’, 36: ‘registration’, 37: ‘renewal’, 38: ‘mortgage order’, 39: ‘effects of ’mortgage with respect to the third buyer’, 40: ‘effects of the mortgage with respect to the third employer’, 41: ‘reduction of mortgages’, 42: ‘repayment of mortgages’, 43: ‘cancellation of registration’, 44: ‘way to release the assets from mortgages’, 45: ‘renunciation and abstention of the creditor in forced expropriation’, 46: ‘means of preserving the patrimonial guarantee’, 47: ‘subrogation action’, 48: ‘revocatory action’, 49: ‘conservative seizure’, 50: ‘judicial protection of rights’, 51: ‘forced execution ’, 52: ‘expropriation’, 53: ‘effects of foreclosure’, 54: ‘effects of forced sale and assignment’, 55: ‘expropriation of assets subject to restrictions of unavailability or free disposal’, 56: ‘specific forced execution’, 57: ‘prescription and forfeiture’, 58: ‘prescription’, 59: ‘suspension of prescription’, 60: ‘termination of prescription’, 61: ‘limitation period of prescription’, 62: ‘ordinary prescription’, 63: ‘short prescription’, 64: ‘presumptive prescription’, 65: ‘calculation of time limits’, 66: ‘forfeiture’

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