A Statutory Article Retrieval Dataset in French

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Abstract

Statutory article retrieval is the task of automatically retrieving law articles relevant to a legal question. While recent advances in natural language processing have sparked considerable interest in many legal tasks, statutory article retrieval remains primarily untouched due to the scarcity of large-scale and high-quality annotated datasets. To address this bottleneck, we introduce the Belgian Statutory Article Retrieval Dataset (BSARD), which consists of 1,100+ French native legal questions labeled by experienced jurists with relevant articles from a corpus of 22,600+ Belgian law articles. Using BSARD, we benchmark several unsupervised information retrieval methods based on term weighting and pooled embeddings. Our best performing baseline achieves 50.8% R@100, which is promising for the feasibility of the task and indicates that there is still substantial room for improvement. By the specificity of the data domain and addressed task, BSARD presents a unique challenge problem for future research on legal information retrieval.

1 Introduction

Legal issues are an integral part of many people’s lives [1]. However, the majority of citizens have little to no knowledge about their rights and fundamental legal processes [2]. As the Internet has become the primary source of information in response to life problems [3], people increasingly turn to search engines when faced with a legal issue [4]. Nevertheless, the quality of the search engine’s legal help results is currently unsatisfactory, as top results mainly refer people to commercial websites that provide basic information as a way to advertise for-profit services [5]. On average, only one in five persons obtain help from the Internet to clarify or solve their legal issue [1]. As a result, many vulnerable citizens who cannot afford a legal expert’s costly assistance are left unprotected or even exploited. This barrier to accessing legal information creates a clear imbalance within the legal system, preventing the right to equal access to justice for all.

People do not need legal services in and of themselves, they need the ends that legal services can provide. Recent advances in natural language processing (NLP), combined with the increasing amount of digitized textual data in the legal domain, offer new possibilities to bridge the gap between people and the law. For example, legal judgment prediction [6,7,8,9,10] may assist citizens in finding insightful patterns between their case and its outcome. Additionally, legal text summarization [11,12] and automated contract review [13,14] may help people clarify long, complex, and ambiguous legal documents. In this work, we focus on statutory article retrieval which, given a legal question – such as “Is it legal to contract a lifetime lease?” – aims to return one or several relevant law articles from a body of legal statutes [15,16], as illustrated in Figure 1. A qualified statutory article retrieval system could provide a professional assisting service for unskilled humans and thereby help empower the weaker parties when used for the public interest.

Finding relevant statutes to a legal question is a challenging task. Unlike traditional ad-hoc information retrieval [17], statutory article retrieval deals with two types of language: common natural language for the questions and complex legal language for the statutes. This difference in language distribution greatly complicates the retrieval task as it indirectly requires an inherent interpretation system that
can translate a natural question from a non-expert to a legal question that can later be matched against statutes. For skilled legal experts, these interpretations come from their knowledge of a question’s topic and domain, and their understanding of the legal concepts and processes involved. Nevertheless, an interpretation is rarely unique. In the end, it is the interpreter’s subjective belief that gives meaning to the question and, accordingly, an idea of the domains in which the answer can be found. In the question “Can I divorce without my spouse’s consent?” for example, one can emphasize the word “divorce” and thereby look for relevant statutes within family law, whereas another may stress the importance of “consent” and consequently search in contract or even privacy law. Hence, the same question can yield different outcomes depending on how one interprets it, making statutory article retrieval even more complex. Lastly, statutory law is not a stack of independent legal articles that can be treated as complete sources of information on their own (unlike news or recipes). Instead, it is a structured and hierarchical collection of legal provisions that have whole meaning only when considered in their overall context, i.e., together with the supplementary information from their neighboring articles, the fields and sub-fields they belong to, and their place in the hierarchy of the law. For instance, assume a construction company intends to terminate the contract with a plumber hired as an independent worker. In most cases, the answer to the question “Can I terminate the employment contract?” can be found in labor law. However, here, the worker may not be an employee and therefore might not fall under labor law rules but must rely on broader contract law rules instead. This simple example illustrates the importance of considering the question’s context and understanding the hierarchical structure of the law when looking for relevant law articles.

In order to study whether retrieval models can approximate the efficiency and reliability of legal experts, we need a suitable labeled dataset. However, such datasets are difficult to obtain considering that, although statutory provisions are generally publicly accessible (yet often not in a machine-readable format), the questions posed by citizens are not. In this paper, we present a novel large-scale French native expert-annotated statutory article retrieval dataset as our main contribution. Our Belgian Statutory Article Retrieval Dataset (BSARD) consists of more than 1,100 legal questions posed by Belgian citizens and labeled by legal experts with references to relevant articles from a corpus of around 22,600 Belgian law articles. As a second contribution, we establish baselines on BSARD by comparing several unsupervised information retrieval approaches based on term weighting and pooled embeddings. The dataset and code are available under a CC BY-NC-SA 4.0 license at https://github.com/maastrichtlawtech/bsard.

## 2 Related work

Due to the increasing digitization of textual legal data, the NLP community has recently introduced more and more datasets to help researchers build reliable models on several legal tasks. For instance, Fawei et al. [18] introduced a legal question answering (LQA) dataset with 400 multi-choices questions based on the US national bar exam. Similarly, Zhong et al. [19] released a LQA dataset ...

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*Figure 1: Illustration of the statutory article retrieval task performed on the Belgian Statutory Article Retrieval Dataset (BSARD), which consists of 1,100+ questions carefully labeled by legal experts with references to relevant articles from the Belgian legislation. With BSARD, models can learn to retrieve law articles relevant to a legal question automatically. All examples we show in the paper are translated from French for illustration.*
based on the Chinese bar exam consisting of 26,365 multiple-choice questions, together with a database of evidence that includes 3,382 Chinese legal provisions and the content of the national examination counseling book. Furthermore, Duan et al. \[20\] proposed a legal reading comprehension dataset with 52,000 question-answer pairs crafted on the fact descriptions of 10,000 cases from the Supreme People’s Court of China. On a different note, Xiao et al. \[21\] presented a dataset for legal judgment prediction (LJP) with around 2.68 million Chinese criminal cases annotated with 183 law articles and 202 charges. Likewise, Chalkidis et al. \[22\] introduced a LJP dataset consisting of 11,478 English cases from the European Court of Human Rights labeled with the corresponding final decision. Meanwhile, Xiao et al. \[23\] introduced a dataset for similar case matching with 8,964 triplets of cases published by the Supreme People’s Court of China, and Chalkidis et al. \[24\] released a text classification dataset containing 57,000 English EU legislative documents tagged with 4,271 labels from the European Vocabulary. Additionally, Manor and Li \[25\] introduced a legal text summarization dataset consisting of 446 sets of contract sections and corresponding reference summaries, and Holzenberger et al. \[26\] presented a statutory reasoning dataset based on US tax law. Recently, Hendrycks et al. \[27\] proposed a dataset for legal contract review that includes 510 contracts annotated with 41 different label clauses for a total of 13,101 annotations. Lastly, the COLIEE Case Law Corpus \[28\] is a case law retrieval and entailment dataset that includes 650 base cases from the Federal Court of Canada, each with 200 candidate cases to be identified as relevant w.r.t. to the base case.

Regarding statutory article retrieval, the only other publicly available dataset related to our work is the COLIEE Statute Law Corpus \[28\], which comprises 696 questions from the Japanese legal bar exam labeled with references to relevant articles from the Japanese Civil Code, where both the questions and articles have been translated from Japanese to English. However, this dataset focuses on legal bar exam question answering, which is quite different from legal questions posed by ordinary citizens. While the latter tend to be vague and straightforward, bar exam questions are meant for aspiring lawyers and are thus specific and advanced. Besides, the dataset only contains closed questions (i.e., questions whose expected answer is either “yes” or “no”) and considers almost 30 times fewer law articles than BSARD. Lastly, unlike BSARD, the data are not native sentences but instead translated from a foreign language with a completely different legal system. As a result, the translated dataset may not accurately reflect the logic of the original legal system and language. These limitations suggest the need for a novel large-scale citizen-centric native dataset for statutory article retrieval, which is the core contribution of the present work.

3 The Belgian Statutory Article Retrieval Dataset

3.1 Dataset collection

We create our dataset in four stages: (i) compiling a large corpus of Belgian law articles, (ii) gathering legal questions with references to relevant law articles, (iii) refining these questions, and (iv) matching the references to the corresponding articles of our corpus.

Law articles collection. In civil law jurisdictions, a legal code is a type of legislation that purports to exhaustively cover a whole area of law, such as criminal law or tax law, by gathering and restating all the written laws in that area into a unique book. Hence, these books constitute valuable resources to collect a large number of law articles on various subjects. We consider 32 publicly available Belgian codes, as presented in Table 1. Together with the legal articles, we extract the corresponding headings of the sections in which these articles appear (i.e., book, part, act, chapter, section, and subsection names). These headings provide an overview of each article’s subject. As pre-processing, we use regular expressions to clean up the articles of specific wording indicating a change in part of the article by a past law (e.g., nested brackets, superscripts, or footnotes). Additionally, we identify and remove the articles repealed by past laws but still present in the codes. Eventually, we end up with a corpus $\mathcal{C} = \{a_1, \cdots, a_N\}$ of $N = 22,633$ articles that we use as our basic retrieval units.

\[1\]Japan is a civil law country that relies predominantly on the rules written down in statutes, whereas most English-speaking countries (e.g., US, UK, Canada and Australia) have a common law system that relies predominantly on past judicial decisions, known as precedents.

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Table 1: Summary of the number of articles collected (after pre-processing) from each of the Belgian codes considered for BSARD, as well as the number of articles found to be relevant for at least one of the legal questions.

| Authority         | Code                                               | #Articles | #Relevant |
|-------------------|----------------------------------------------------|-----------|-----------|
| Federal           | Judicial Code                                     | 2285      | 429       |
|                   | Code of Economic Law                              | 2032      | 98        |
|                   | Civil Code                                         | 1961      | 568       |
|                   | Code of Workplace Welfare                         | 1287      | 25        |
|                   | Code of Companies and Associations                 | 1194      | 0         |
|                   | Code of Local Democracy and Decentralization      | 1159      | 3         |
|                   | Navigation Code                                    | 977       | 0         |
|                   | Code of Criminal Instruction                       | 719       | 155       |
|                   | Penal Code                                         | 689       | 154       |
|                   | Social Penal Code                                  | 307       | 23        |
|                   | Forestry Code                                      | 261       | 0         |
|                   | Railway Code                                       | 260       | 0         |
|                   | Electoral Code                                     | 218       | 0         |
|                   | The Constitution                                   | 208       | 5         |
|                   | Code of Various Rights and Taxes                   | 191       | 0         |
|                   | Code of Private International Law                  | 135       | 4         |
|                   | Consular Code                                      | 100       | 0         |
|                   | Rural Code                                         | 87        | 12        |
|                   | Military Penal Code                                | 66        | 1         |
|                   | Code of Belgian Nationality                        | 31        | 8         |
| Regional          | Walloon Code of Social Action and Health           | 3650      | 40        |
|                   | Walloon Code of the Environment                    | 1270      | 22        |
|                   | Walloon Code of Territorial Development            | 796       | 0         |
|                   | Walloon Public Service Code                        | 597       | 0         |
|                   | Walloon Code of Agriculture                        | 461       | 0         |
|                   | Brussels Spatial Planning Code                     | 401       | 1         |
|                   | Walloon Code of Basic and Secondary Education      | 310       | 0         |
|                   | Walloon Code of Sustainable Housing                | 286       | 20        |
|                   | Brussels Housing Code                              | 279       | 44        |
|                   | Brussels Code of Air, Climate and Energy Management| 208       | 0         |
|                   | Walloon Animal Welfare Code                        | 108       | 0         |
|                   | Brussels Municipal Electoral Code                  | 100       | 0         |
|                   |                                                    | 22633     | 1612      |

Legal questions collection. We partner with Droits Quotidiens (DQ), a Belgian non-profit association that offers to answer legal questions from Belgian citizens. Each year, DQ receives and collects around 4,000 questions posed by non-legal people about a legal issue. Their team of six experienced jurists regularly answers the latest, most frequently asked questions from their database. Specifically, their legal clarification process consists of three steps. First, they reword the selected question in a clear and anonymized model question. Then, they search the Belgian law for articles that help in answering the question and reference them. Finally, they explain these relevant articles and answer the question so that a non-legal expert can understand them. These questions, legal references, and answers are further categorized before being posted on DQ’s website. For instance, the question “What is the seizure of goods?” is tagged under the “Money > Debt recovery” category. With their help, we collect more than 3,200 questions together with their references to relevant law articles and categorization tags.

Questions refinement. We find that around one-third of the collected questions are duplicates. However, these duplicated questions come with different categorization tags, some of which providing additional context that can be used to refine the questions. For example, the question “Should I install fire detectors?” appears four times with the following different tags: “Housing > Rent > I am a x > In y”, where $x \in \{\text{tenant, landlord}\}$ and $y \in \{\text{Wallonia, Brussels}\}$. We distinguish between the tags indicating a question subject (e.g., “housing” or “rent”) and those that provide context about personal.

[^1]: www.droitsquotidiens.be
Table 2: Distribution of question topics in BSARD.

| General topic | Percentage | Subtopics | Example                      |
|---------------|------------|-----------|------------------------------|
| Family        | 30.6%      | Marriage, parentage, divorce, etc. | When is there a guardianship? |
| Housing       | 27.4%      | Rental, flatshare, insalubrity, etc. | Who should repair the common wall? |
| Money         | 16.0%      | Debts, insurance, taxes, etc. | What is the seizure of goods? |
| Justice       | 13.6%      | Proceedings, crimes, legal aid, etc. | How does the appeal process work? |
| Foreigners    | 5.7%       | Citizenship, illegal stay, etc. | Can I come to Belgium to get married? |
| Social security | 3.5%    | Pensions, pregnancy, health, etc. | Am I dismissed during my pregnancy? |
| Work          | 3.2%       | Breach of contract, injuries, etc. | Can I miss work to visit the doctor? |

(a) Question length.  (b) Article length.  (c) Number of relevant articles per question.  (d) Number of citations per relevant article.

Figure 2: Statistics of BSARD.

situation and/or location. If any, we append the contextual tags in front of the question, which solves most of the duplicates problem and greatly improves the overall quality of the questions by adding a specific context. For instance, one refinement of the above question is given by “I am a tenant in Brussels. Should I install fire detectors?”.

Questions labeling. The collected questions are annotated with plain text references to relevant law articles (e.g., “Article 8 of the Civil Code”). We use regular expressions to parse these references and match them to the corresponding articles from our corpus. First, we filter out questions whose references are not articles (e.g., an entire decree or order). Then, we remove questions with references to legal acts other than codes of law (e.g., decrees, directives, or ordinances). Lastly, we ignore questions with references to codes other than those we initially considered. We eventually end up with 1,108 questions, each carefully labeled with the ids of the corresponding relevant law articles from our corpus.

3.2 Dataset analysis

To provide more insight, we describe quantitative and qualitative observations about BSARD. Specifically, we explore (i) the diversity in questions and articles, (ii) the relationship between questions and their relevant articles, and (iii) the type of reasoning required to retrieve relevant articles.

Diversity. The 22,633 law articles that constitute our corpus have been collected from 32 Belgian codes covering a large number of legal topics, as shown in Table 1. The articles have a median length of 495 words, but 25% of them contain more than 1,026 words, and 40 articles exceed 10,000 words (the lengthiest one being up to 39,566 words), as illustrated in Figure 2b. These long articles are mostly general provisions, i.e., articles that appear at the beginning of a code and define many terms and concepts later mentioned in the code. The questions are between 23 and 262 words long, with a median of 83 words, as shown in Figure 2a. They cover a wide range of topics, with around 85% of them being either about family, housing, money, or justice, while the remaining 15% concern either social security, foreigners, or work, as described in Table 2.
Question-article relationship. Questions might have one or several relevant legal articles. Overall, 75% of the questions have less than five relevant articles, 18% have between 5 and 20, and the remaining 7% have more than 20 with a maximum of 109, as seen in Figure 2c. The latter often have complex and indirect answers that demand extensive reasoning over a whole code section, which explains these large numbers of relevant articles. Furthermore, an article that is deemed relevant to one question might also be for some other ones. Therefore, we calculate for each unique article deemed relevant to at least one question the total number of times it is cited as a legal reference across all questions. We find that the median number of citations for those articles is 2, and less than 25% of them are cited more than five times, as illustrated in Figure 2d. Hence, out of the 22633 articles, only 1612 are referred to as relevant to at least one question in the dataset, and around 80% of these 1612 articles come from either the Civil Code, Judicial Code, Criminal Investigation Code, or Penal Code. Meanwhile, 18 out of the 32 codes have less than five articles mentioned as relevant to at least one question, which can be explained by the fact that those codes focus less on individuals and their concerns.

Retrieval process of legal experts. To get a better understanding of the reasoning followed by legal experts when approaching the statutory article retrieval task, we sample a few questions from our dataset and ask a legal scholar who is not familiar with Belgian law (and therefore has no past knowledge of the location of articles covering a particular subject) to retrieve relevant articles to these questions. In what follows, we summarize the approach used by this expert. First, the expert determines whether the issue involves private or public law. To distinguish between the two, one must identify to whom the rules apply (i.e., the parties involved in the issue that hold the rights or duties). Generally speaking, public law deals with issues that affect the general public or state (i.e., society as a whole), whereas private law concerns disputes of private matters between individuals, families, and businesses. This first step allows the expert to make an initial selection among the codes of law, which generally relate to only one of either private or public law. Next, the expert refines his search by determining the field of law concerned (e.g., contract law), followed by the sub-field (e.g., tenant law), and so on, until having a set of potentially relevant codes in the question’s domains. Then, the expert focuses on the table of contents of one of the selected codes and undertakes a hierarchical search that starts from the books’ headings and progressively extends to its chapters, sections, and subsections, respectively. This step allows to filter out many irrelevant articles by analyzing the connection between the question’s subject and the different sections’ headings. Finally, the expert explores the articles within the sections deemed potentially relevant to the question in search of the expected answer. If at any point of the process the expert realizes that the chosen direction leads to no end, he steps back to the previous higher level of the hierarchy, chooses another potentially relevant direction, and starts narrowing down his search from there. From this analysis, we conclude that legal experts rely heavily on the hierarchy of the law when retrieving relevant articles to a legal question, which indicates that the chapter, section, and subsection headings carry valuable information that retrieval systems should probably consider.

4 Methods

Formally speaking, a statutory article retrieval system \( R : (q, C) \rightarrow F \) is a function that takes as input a question \( q \) along with a corpus of law articles \( C \), and returns a much smaller filter set \( F \subset C \) of the supposedly relevant articles, ranked by decreasing order of relevance. For a fixed \( k = |F| \ll |C| \), the retriever can be evaluated in isolation with multiple rank-based metrics (see Section 5.1). We compare several unsupervised information retrieval approaches based on term weighting and pooled embeddings as benchmark methods for the task.

4.1 Term weighting

In the context of statutory article retrieval, a term weighting model may be defined as a scoring function \( S : (q, a) \rightarrow \mathbb{R}_+ \) that takes as inputs a question \( q \) and an article \( a \in C \) and returns a relevance score between the two, i.e.,

\[
S(q, a) = \sum_{t \in q} w(t, a),
\]

\( ^\text{3} \)Gijs Van Dijck, Professor of Private Law at Maastricht University.
where \( w(t, a) \) is the weight of article \( a \) for query term \( t \). We first use a simple TF-IDF weighting scheme such that

\[
w(t, a) = tf(t, a) \cdot \log \frac{|C|}{df(t)},
\]

where the term frequency (tf) is the number of occurrences of term \( t \) in article \( a \), and the document frequency (df) is the number of articles within the corpus that contain term \( t \). We then experiment with the official BM25 weighting formula \([29]\), defined as

\[
w(t, a) = \frac{tf(t, a) \cdot (k_1 + 1)}{tf(t, a) + k_1 \cdot (1 - b + b \cdot \frac{|a|}{avgal})} \cdot \log \frac{|C| - df(t) + 0.5}{df(t) + 0.5},
\]

where \( k_1 \in \mathbb{R}_+ \) and \( b \in [0, 1] \) are constant parameters to be fixed, \( |a| \) is the article length, and \( avgal \) is the average article length in the collection.

During inference, we compute a score for each article in corpus \( C \) and return the \( k \) articles with the highest scores as the top-\( k \) most relevant results to the input query.

### 4.2 Unsupervised pooled embeddings

A word embedding model \( E : \mathcal{W} \rightarrow \mathbb{R}^d \) is a parameterized function that maps words \( t \in \mathcal{W} \) to high-dimensional real-valued vectors of size \( d \). Given the word representations of a text passage, a pooling operation \( \text{pool} : \mathbb{R}^{n \times d} \rightarrow \mathbb{R}^d \) can be applied to distill a global representation for the passage. Using a distance function \( \text{dist} : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}_+ \), the pooled representations of two different sequences (e.g., a question and an article) can be compared such that the resulting value acts as a relevance score between the sequences. Based on existing literature \([40]\) and the intuition that unsupervised pooled representations from word embedding models do not explicitly optimize for retrieval, we do not expect these to be strong baselines, but we include them for comparison.

We compare with two types of widely-used unsupervised word representations: (1) context-independent embeddings from simple feed-forward neural networks such as word2vec \([31, 32]\) and fastText \([33]\), and (2) context-dependent embeddings from BERT-based models \([34]\). Note that the latter models can process texts up to a maximum input length of 512 tokens (i.e., terms or sub-terms, depending on the tokenizer). Although alternative models exist to alleviate this limitation \([35, 36, 37]\), we use a simpler workaround that consists of splitting the text into overlapping chunks and passing each chunk in turn to the embedding model. To form the chunks, we consider contiguous text sequences of 200 tokens with an overlap of 20 tokens between two consecutive chunks. See Appendix A.1 for further details on the BERT-based embeddings we use. For all models, we experiment with various pooling operations (\( \text{mean}, \text{max}, \text{and sum} \)), and distance functions (\( L_2 \) and \( \cos \)).

During inference, we pre-encode our corpus of articles offline and store the articles’ representations in an index structure. Then, given a new query, we perform a brute-force search by computing the distances between the query representation and the pre-encoded article representations. The resulting distances are used to rank the articles such that the \( k \) articles that have the lowest distances with the query are returned as the top-\( k \) most relevant results.

## 5 Experiments

We benchmark the unsupervised information retrieval approaches described in Section 4 and perform several analyses to better understand the factors that contribute to the methods performance.

### 5.1 Experimental setup

**Metrics.** We use three standard information retrieval metrics \([38]\) to evaluate performance, namely the (macro-averaged) recall@\( k \) (R@k), mean reciprocal rank@\( k \) (MRR@k), and mean average precision@\( k \) (MAP@k). See Appendix A.2 for a detailed description of these metrics in the context of statutory article retrieval. We deliberately omit to report the precision@\( k \) given that questions have a variable number of relevant articles (as illustrated in Figure 2c), and therefore reporting that metrics at a fixed \( k \) would not be meaningful (e.g., questions with a unique relevant article would always have a P@\( k \leq 0.5 \) if \( k > 1 \)). We use \( k \in \{20, 50, 100\} \) for our evaluation.
Table 3: Performance of several unsupervised information retrieval methods on BSARD (test set). The results of our best performing baseline (in bold) suggests ample opportunity for improvement.

| Model                  | MRR@100 | MAP@100 | R@20 | R@50 | R@100 |
|------------------------|---------|---------|------|------|-------|
| Term weighting         |         |         |      |      |       |
| TF-IDF                 | 13.90   | 9.14    | 23.76| 32.35| 39.05 |
| BM25 (official)        | 23.81   | 14.95   | 31.54| 42.96| 50.75 |
| Unsupervised pooled embeddings |         |         |      |      |       |
| word2vec               | 21.93   | 13.17   | 28.87| 41.07| 49.55 |
| fastText               | 5.58    | 2.02    | 7.21 | 10.71| 14.05 |
| BERT-based             | 1.56    | 0.25    | 0.47 | 0.78 | 0.96  |

Models. Regarding the pooled embeddings, we experiment with several word2vec models pre-trained on domain-general text [39], one fastText CBOW model with an embedding size of 300 pre-trained on French webpages and a number of pre-trained French or multilingual BERT-based models available from the HuggingFace Transformers library [40], namely CamemBERT [41], FlauBERT [42], mBERT [34], and DistilmBERT [43].

Hyper-parameters. For each embedding model, we experiment with mean, max, and sum pooling to distill a global representation for a passage, as well as euclidean and cosine distances to compare passage representations. We split the questions into training/test sets with 886 and 222 questions, respectively. Table 4 in Appendix A shows the performance of our models on the train set, which is treated as a development set since no training is involved. We select the best performing word2vec, fastText, and BERT-based models (see Appendix A.3 for details), and compare them with the term weighting methods on the test set in Section 5.2. Regarding our BM25 model, we use $k_1 = 1.2$ and $b = 0.75$, following the settings recommended by Jones et al. [44].

Schedule. Our experiments are run using a single Tesla V100 GPU with 32 GBs of memory on a server with one Intel Xeon Processor E5-2698 v4 that has 20 physical cores and 512 GBs of RAM.

5.2 Results

Table 3 shows the performance of our models on the test set. The term weighting models show reasonable performance across all metrics, with BM25 significantly improving over TF-IDF by roughly 10% on MRR@100 and R@100. To put BM25 results into perspective, a R@100 of 50.75% can be interpreted as the model retrieving slightly more than half of all the relevant articles to a query when considering the top-100 results. Furthermore, a MRR@100 of 23.81% means that, on average, the first relevant article retrieved by the model appears at the fourth position in the ranked results list. Regarding the models based on unsupervised pooled representations, that which uses word2vec embeddings significantly outperforms the ones using fastText and BERT embeddings, suggesting that word-level embeddings are more appropriate for the task than character-level or subword-level embeddings when used in an unsupervised setting.

Surprisingly, our model based on pooled BERT-based embeddings shows poor performance. After some analysis, we observe that this model has the largest percentage of out-of-vocabulary (OOV) words, where 89.9% of the words from the legal questions and articles are not present as is (i.e., as full words) in its original vocabulary. By comparison, that number drops to 25.4% for word2vec and 13.3% for fastText. The high OOV percentage of the BERT-based model results in it splitting most of the input words into subwords from its vocabulary, which are less specific and cause a loss of information on the initial meaning of the given words. Additionally, we notice that the pooled BERT-based embeddings are particularly sensitive to the length of the text sequences being compared. Indeed, after comparing the respective lengths of the questions and corresponding articles retrieved by the model, we observe that most of the top-$k$ articles tend to be close in length to the question (the length of the retrieved articles increases as $k$ increases), often at the expense of the article’s relevance to that question. These findings can explain the poor performance of the model.

4 [https://fasttext.cc/docs/en/crawl-vectors.html](https://fasttext.cc/docs/en/crawl-vectors.html)
In summary, we find that BM25 performs best among all our tested baselines with a R@100 of 50.75%, although the unsupervised word2vec-based model gives quite close results (1.2% R@100 difference). Nevertheless, assuming that a skilled legal expert can eventually retrieve all relevant articles to any question (and thus get perfect scores), our results suggest ample opportunity for improvement.

6 Discussion

We discuss the limitations and broader impacts of BSARD, as well as our plans for future work.

Limitations. As our dataset aims to give researchers a well-defined benchmark to evaluate existing and future legal information retrieval models, certain limitations need to be borne in mind to avoid drawing erroneous conclusions. First, the collected articles are limited to those found in the considered Belgian codes, which obviously does not cover the entire Belgian law as thousands of articles from decrees, directives, and ordinances are missing. During our dataset construction process, all references to these uncollected articles are ignored, which causes some questions to end up with only a fraction of their initial number of relevant articles. This information loss implies that the answer contained in the remaining relevant articles is probably incomplete, although it is still perfectly appropriate. Additionally, it is essential to note that not all legal questions can be answered with statutes alone. For instance, let us assume the following one: “Can I evict my tenants if they make too much noise?”.

In that case, there might not be a detailed answer within the statutory law that quantifies a specific noise threshold at which eviction is allowed. Instead, the landlord should probably rely more on case law and find precedents similar to their current situation (e.g., the tenant makes two parties a week until 2 am). Thus, some questions are better suited than others to the statutory article retrieval task, and the domain of the less suitable ones remains to be determined.

Broader impacts. In addition to helping advance the state-of-the-art in retrieving statutes relevant to a legal question, BSARD-based models could improve the efficiency of the legal information retrieval process in the context of legal research, therefore enabling researchers to devote themselves to more thoughtful parts of their research. Furthermore, BSARD can become a starting point of new open-source legal information search tools so that the socially weaker parties to disputes can benefit from a free professional assisting service. However, there are risks that the dataset will not be used exclusively for the public interest but perhaps also for profit as part of proprietary search tools developed by companies. Since this would reinforce rather than solve the problem of access to legal information and justice for all, we decided to distribute BSARD under a license with a non-commercial clause, namely the [CC BY-NC-SA 4.0](https://creativecommons.org/licenses/by-nc-sa/4.0/). Other potential negative societal impacts could involve using BSARD-based models to misuse or find gaps within the governmental laws or use these models not to defend oneself but to deliberately damage people or companies instead. Of course, we discourage anyone from developing models that aim to perform the latter actions.

Future work. In the future, we plan to explore more supervised neural IR techniques on BSARD, in particular dense retrieval models [45], and investigate how to exploit the hierarchy of the law in retrieval systems. We also plan to extend our dataset by collecting additional law articles from other legal sources, namely decrees, directives, and ordinances. As a result, BSARD v2.0 will have an extra 1,860 annotated legal questions, and all questions of that new version will come with their complete list of relevant law articles. In parallel, we are working with Droits Quotidiens on a Dutch version of BSARD that should contain around 1,000 Dutch native legal questions posed by Flemish citizens.

7 Conclusion

In this paper, we present the Belgian Statutory Article Retrieval Dataset (BSARD), a large-scale citizen-centric French native dataset for statutory article retrieval. Within a larger effort to bridge the gap between people and the law, BSARD provides a means of evaluating and developing models capable of automatically retrieving law articles relevant to a legal question posed by a layperson. We benchmark several unsupervised information retrieval methods that show promise for the feasibility of the task, yet indicate substantial room for improvement. Above all, we hope that our work sparks interest in developing practical and reliable statutory article retrieval models to help improve access to justice for all.
Acknowledgments

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Appendix

A Implementation details

A.1 BERT-based embeddings

Regarding which outputs from the pre-trained BERT-based models to use as word embeddings, we follow the recommendations given by Han Xiao, creator of the open-source project bert-as-service [46], who experimented with different approaches and shared some conclusions and rationale on the FAQ page of the project.[47] In summary, Xiao recommends using the outputs from the second-to-last hidden layer of the models. Indeed, the last hidden layer is too close to the training output, and therefore might be biased by the training target functions (i.e., masked language modeling and next sentence prediction). On the other hand, the first hidden layer might be too close to initial token embeddings and will probably preserve the very original word information (i.e., very little self-attention involved). Therefore, any layer between the first and last ones (excluded) represents a trade-off between the two situations described above. The second-to-last layer is what Xiao settled on as a reasonable “sweet spot”. He also mentions that, although the hidden state of [CLS] acts as a meaningful “aggregate representation” of an input text sequence when the model has been fine-tuned on a downstream classification task, this is not especially true when using out-of-the-box pre-trained embeddings.

A.2 Evaluation metrics

Let \( \text{rel}_q(a) \in \{0, 1\} \) be the binary relevance label of article \( a \) for question \( q \), and \( \langle i, a \rangle \in \mathcal{F}_q \) a result tuple (article \( a \) at rank \( i \)) from the filter set \( \mathcal{F}_q \subset \mathcal{C} \) of ranked articles retrieved for question \( q \).

Recall. The recall \( R_q \) is the fraction of relevant articles retrieved for query \( q \) w.r.t. the total number of relevant articles in the corpus \( \mathcal{C} \), i.e.,

\[
R_q = \frac{\sum_{\langle i, a \rangle \in \mathcal{F}_q} \text{rel}_q(a)}{\sum_{a \in \mathcal{C}} \text{rel}_q(a)}. \tag{4}
\]

Reciprocal rank. The reciprocal rank \( \text{RR}_q \) calculates the reciprocal of the rank at which the first relevant article is retrieved, i.e.,

\[
\text{RR}_q = \max_{\langle i, a \rangle \in \mathcal{F}_q} \frac{\text{rel}_q(a)}{i}. \tag{5}
\]

Average precision. The average precision \( \text{AP}_q \) is the mean of the precision value obtained after each relevant article is retrieved, that is

\[
\text{AP}_q = \frac{\sum_{\langle i, a \rangle \in \mathcal{F}_q} \text{P}_{q,i} \times \text{rel}_q(a)}{\sum_{a \in \mathcal{C}} \text{rel}_q(a)}, \tag{6}
\]

[46] Han Xiao. Serving google bert in production using tensor-flow and zeromq. 2019. URL https://hanxiao.io/2019/01/02/Serving-Google-BERT-in-Production-using-Tensorflow-and-ZeroMQ.

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5 https://github.com/hanxiao/bert-as-service#speech_balloons-faq
where \( P_{q,j} \) is the precision computed at rank \( j \) for query \( q \), i.e., the fraction of relevant articles retrieved for query \( q \) w.r.t. the total number of articles in the retrieved set \( \{ F_q \}_{i=1}^j \):

\[
P_{q,j} = \frac{\sum_{(i,a) \in \{ F_q \}_{i=1}^j} \text{rel}_q(a)}{|\{ F_q \}_{i=1}^j|}.
\] (7)

We report the macro-averaged recall (R), mean reciprocal rank (MRR), and mean average precision (MAP), which are the average values of the corresponding metrics over a set of \( n \) queries. Note that as those metrics are computed for a filter set of size \( k = |F_q| \ll |C| \) (and not on the entire list of articles in \( \mathcal{C} \)), we report them with the suffix “\(@k\)”. 

A.3 Hyper-parameters search

Table 4 shows the MRR@100 results of all tested models on BSARD train set. The best performing models per model type are:

- **word2vec**: skip-gram model pre-trained on the lemmatized frWaC corpus with an embedding size of 500, mean (or sum) pooling and cosine distance;
- **fastText**: mean (or sum) pooling and cosine distance;
- **BERT-based**: DistilmBERT with max-pooling and cosine distance.

B Supplemental materials

**Documentation.** As a first way to document our dataset, we include the data statement \([47]\) for BSARD, which provides detailed context on the dataset so that researchers, developers, and users can understand how models built upon it might generalize, be appropriately deployed, and potentially reflect bias or exclusion.

- **Curation rationale**: All law articles from the selected Belgian codes were included in our dataset, except those revoked (identifiable because mentioned before the article or empty content) and those with a duplicate number within the same code (namely, the articles from Act V, Book III of the Civil Code; from Sections 2, 2bis, and 3 of Chapter II, Act VIII, Book III of the Civil Code; from Act XVIII, Book III of the Civil Code; from the Preliminary Act of the Code of Criminal Instruction; from the Appendix of the Judicial Code). Not including the latter articles did not pose a strong concern because none of them were mentioned as relevant to any of the questions in our dataset. Regarding the questions, all those that referenced at least one of the articles from our corpus were included in the dataset.

- **Language variety**: The questions and legal articles were collected in French (fr-BE) as spoken in Wallonia and Brussels-Capital region.

- **Speaker demographic**: Speakers were not directly approached for inclusion in this dataset and thus could not be asked for demographic information. Questions were collected, anonymized, and reformulated by Droits Quotidiens. Therefore, no direct information is available about the speakers’ age and gender distribution or socioeconomic status. However, it is expected that most, but not all, of the speakers are adults (18+ years), speak French as a native language, and live in Wallonia or Brussels-Capital region.

- **Annotator demographic**: A total of six Belgian jurists from Droits Quotidiens contributed to annotating the questions. All have a law degree from a Belgian university and years of experience in providing legal advice and clarifications of the law. They ranged in age from 30-60 years, including one man and five women, gave their ethnicity as white European, speak French as a native language, and represent upper middle class based on income levels.

- **Speech situation**: All the questions were written between 2018 and 2021 and collected in May 2021. They represent informal, asynchronous, edited, written language that does not exceed 265 words. None of the questions contained hateful, aggressive, or inappropriate content.

\[\text{https://dumps.wikimedia.org/frwiki}\]
\[\text{http://wacky.sslmit.unibo.it/doku.php?id=corpora#french}\]
Table 4: Mean Reciprocal Rank (MRR) results on BSARD train set. Each model retrieves the top-100 articles per question directly from the entire 22.6k article collection. Best results appear in bold.

| Model       | Dataset | Method | Embedding Dimension | Distance Function | Distance | Pooling  | Pooling  |
|-------------|---------|--------|---------------------|-------------------|----------|----------|----------|
|             |         |        |                     |                   | mean     | max      | sum      |
| word2vec    | frWiki  | CBOW   | 1000                | cosine            | 4.59     | 1.29     | 4.59     |
|             |         |        |                     | euclidean         | 4.63     | 1.42     | 1.26     |
|             |         | CBOW   | 1000                | cosine            | 19.35    | 8.30     | 19.35    |
|             |         |        |                     | euclidean         | 20.67    | 3.70     | 2.00     |
|             | frWac   | CBOW   | 200                 | cosine            | 15.38    | 6.61     | 15.38    |
|             |         |        |                     | euclidean         | 17.13    | 4.42     | 3.17     |
|             |         | CBOW   | 200                 | cosine            | 16.07    | 8.49     | 16.07    |
|             |         |        |                     | euclidean         | 15.95    | 5.32     | 3.26     |
|             |         |        |                     |                   | 19.77    | 10.57    | 19.77    |
|             |         |        |                     |                   | 19.16    | 5.08     | 3.56     |
|             |         | CBOW   | 700                 | cosine            | 18.00    | 7.73     | 18.00    |
|             |         |        |                     | euclidean         | 18.80    | 3.32     | 2.30     |
|             |         |         |                     | cosine            | 19.01    | 9.05     | 19.01    |
|             |         |        |                     | euclidean         | 19.87    | 3.25     | 2.16     |
|             |         | CBOW   | 700                 | cosine            | 18.46    | 8.96     | 18.46    |
|             |         |        |                     | euclidean         | 18.93    | 2.86     | 2.84     |
|             |         | CBOW   | 1000                | cosine            | 16.65    | 10.94    | 16.65    |
|             |         |        |                     | euclidean         | 17.28    | 5.75     | 2.14     |
|             |         | CBOW   | 700                 | cosine            | 19.55    | 7.53     | 19.55    |
|             |         |        |                     | euclidean         | 19.49    | 3.83     | 3.72     |
|             |         | CBOW   | 700                 | cosine            | 18.46    | 8.96     | 18.46    |
|             |         |        |                     | euclidean         | 18.93    | 2.86     | 2.84     |
| fastText    | N/A.    | CBOW   | 300                 | cosine            | 13.20    | 2.50     | 13.20    |
|             |         |        |                     | euclidean         | 12.28    | 2.33     | 2.14     |
| CamemBERT   | N/A.    | N/A.   | 768                 | cosine            | 0.64     | 0.41     | 0.64     |
|             |         |        |                     | euclidean         | 0.57     | 0.39     | 0.57     |
| FlauBERT    | N/A.    | N/A.   | 768                 | cosine            | 0.62     | 0.60     | 0.62     |
|             |         |        |                     | euclidean         | 0.38     | 0.59     | 0.38     |
| mBERT       | N/A.    | N/A.   | 768                 | cosine            | 0.29     | 0.50     | 0.29     |
|             |         |        |                     | euclidean         | 0.33     | 0.38     | 0.33     |
| DistilmBERT | N/A.    | N/A.   | 768                 | cosine            | 0.19     | 2.31     | 0.18     |
|             |         |        |                     | euclidean         | 0.16     | 1.63     | 0.16     |

language as they were all reviewed and reworded by Droits Quotidiens to be neutral, anonymous, and comprehensive. All the legal articles were written between 1804 and 2021 and collected in May 2021. They represent strong, formal, written language that can contain up to 39,570 words.

- Text characteristics: Many articles complement or rely on other articles in the same or another code and thus contain (sometimes lengthy) legal references, which might be seen as noisy data.
- Recording quality: N/A.
- Other: N/A.
- Provenance appendix: N/A.

In addition to the data statement, we provide the dataset nutrition labels [48] for BSARD in Table 5.

Intended uses. The dataset is intended to be used by researchers to build and evaluate models on retrieving law articles relevant to an input legal question. It should not be regarded as a reliable source of legal information at this point in time, as both the questions and articles correspond to an outdated version of the Belgian law from May 2021 (time of dataset collection). In the latter case, the user is advised to consult daily updated official legal resources (e.g., the Belgian Official Gazette).
Table 5: Dataset nutrition labels for BSARD.

### Data Facts
Belgian Statutory Article Retrieval Dataset (BSARD)

### Metadata
| Filename          | articles_fr.csv† |
|-------------------|------------------|
|                   | questions_fr_train.csv† |
|                   | questions_fr_test.csv‡ |
| Format            | CSV              |
| Url               | https://doi.org/10.5281/zenodo.5217310 |
| Domain            | natural language processing |
| Keywords          | information retrieval, law |
| Type              | tabular          |
| Rows              | 22633∗, 886†, 222‡ |
| Columns           | 6∗, 6†, 6‡ |
| Missing           | none             |
| License           | CC BY-NC-SA 4.0  |
| Released          | August 2021      |
| Range             | N/A              |

**Description**: This dataset is a collection of French native legal questions posed by Belgian citizens and law articles from the Belgian legislation. The articles come from 32 publicly available Belgian codes. Each question is labeled by one or several relevant articles from the corpus. The annotations were done by a team of experienced Belgian jurists.

### Variables

| Variables          | Description |
|--------------------|-------------|
| id∗                | A unique ID number for the article. |
| article∗           | The full content of the article. |
| code∗              | The code to which the article belongs. |
| article_no∗        | The article number in the code. |
| description∗       | The concatenated headings of the article. |
| law_type∗          | Either "regional" or "national" law. |
| id†‡               | A unique ID number for the question. |
| question†‡         | The content of the question. |
| category†‡         | The general topic of the question. |
| subcategory†‡      | The precise topic of the question. |
| extra_description†‡| Extra categorization tags of the question. |
| article_ids†‡      | A list of article IDs relevant to the question. |

### Provenance

| Source             | https://www.ejustice.just.fgov.be/loi/loi.htm |
|--------------------|-----------------------------------------------|
| Droits Quotidiens  | https://www.droitsquotidiens.be                |
| Author             | Antoine Louis et al.                           |
| Email              | a.louis@maastrichtuniversity.nl                |

**Hosting.** The dataset is hosted on Github at [https://github.com/maastrichtlawtech/bsard](https://github.com/maastrichtlawtech/bsard) and on Zenodo at [https://doi.org/10.5281/zenodo.5217310](https://doi.org/10.5281/zenodo.5217310).

**Licensing.** The dataset is publicly distributed under a CC BY-NC-SA 4.0 license, which allows to freely share (i.e., copy and redistribute) and adapt (i.e., remix, transform, and build upon) the material on the conditions that the latter is used for non-commercial purposes only, proper attribution is given (i.e., appropriate credit, link to the license, and an indication of changes), and the same license as the original is used if one distribute an adapted version of the material. The code to reproduce the experimental results of the paper is released under the MIT license.

**Maintenance.** The dataset will be supported and maintained by the Law & Tech Lab at Maastricht University. Any updates to the dataset will be communicated via the Github repository. All questions and comments about the dataset can be sent to Antoine Louis: a.louis@maastrichtuniversity.nl. Other contacts can be found at [https://www.maastrichtuniversity.nl/law-and-tech-people](https://www.maastrichtuniversity.nl/law-and-tech-people).

**Data format.** The dataset is stored as CSV files and can be read using standard libraries (e.g., the built-in csv module in Python).
**Reproducibility.** The authors ensure reproducibility of the experimental results by releasing the code within the GitHub repository.

**Responsibility.** The authors bear all responsibility in case of violation of rights, etc., and confirm that the dataset is released under the CC BY-NC-SA 4.0 license.