European Court of Human Right Open Data project

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Abstract This paper presents thirteen datasets for binary, multiclass and multilabel classification based on the European Court of Human Rights judgments since its creation. The interest of such datasets is explained through the prism of the researcher, the data scientist, the citizen and the legal practitioner. Contrarily to many datasets, the creation process, from the collection of raw data to the feature transformation, is provided under the form of a collection of fully automated and open-source scripts. It ensures reproducibility and a high level of confidence in the processed data which is some of the most important issues in data governance nowadays.

Keywords datasets · European Court of Human Rights · open data

1 Introduction

In this paper, we present the European Court of Human Rights Open Data project (ECHR-OD). It aims at providing up-to-date and complete datasets about the European Court of Human Rights decisions since its creation. To be up-to-date and exhaustive, we developed a fully automated process to regenerate the entire datasets from scratch, starting from the collection of raw documents. As a result, the data is as complete as it can be in terms of number of cases. The reproducibility makes it easy to add or remove information in future iterations of the datasets. To be able to check for corrupted data or bias, black swans or outliers, the whole datasets generation process is open-source and versioned. Before presenting the project and datasets, we discuss the importance of data quality and the multiple issues with current datasets in complex fields such as the legal domain.

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It is now well established that the recent and spectacular results of Artificial Intelligence, notably with Deep Learning techniques, are partly due to the availability of data, so called “Big Data”, and the exponential growth of computational power. For a very long time, the bias-variance tradeoff seemed to be an unbeatable problem: complex models reduce the bias but hurt the variance, while simple models lead to high variance. In parallel, the regularization effect of additional data for complex models was also well known as illustrated by Figure 1. Since the advent of Deep Learning, we have discovered how to efficiently build extremely complex models with moderate variance. However, it requires a considerable amount of data to correctly reduce the variance, and there is now a growing consensus on the fact that data are as important as algorithms. In particular, the quality of a model is bounded by the quality of the data it learns from. The availability and quality of data are thus of primary importance for researchers and practitioners.

Fig. 1 The regularization effect of data The ground truth (blue) is a $\sin(x)$ modeled by a polynomial of degree 9 (green). On top, with only 11 training points, the model does not approximate correctly the ground truth while at the bottom, with 100 training points, the model error is far lower.

Beyond the scope of pure scientific interest, the data governance is particularly crucial for our modern societies (Olhede and Wolfe (2018)). What data are publicly available? Who produces manages and manipulates those data? What are the quality of the data? What is the process of collection, curation and transformation? Those are few legitimate questions that a citizen, a company, or an institution may (should?) ask. One can mention the
recent General Data Protection Regulation\footnote{https://www.eugdpr.org/} (GDPR), a European union law with global application, that tries to give a legal framework to address some of the abovementioned questions. Beside privacy and business considerations, the quality of data is at the core of the quality of insights and decisions derived from the data.

The Open Data movement considers that the data should be freely available and reusable by anyone. Although it has strong beneficial effects at many levels \cite{janssen2012open}, I believe this is not enough to insure data quality and to totally handle all those questions. There are many ways data may be unsuitable for taking decisions (either solely human based or assisted by any kind of model):

- **Data sparsity and irrelevant information**: a dataset may lack information to correctly take a decision or on the contrary, contain a lot of irrelevant information. It is hard to know \textit{a priori} what piece of information is useful or not to model or understand a phenomenon. It usually requires an iterative process, several studies to have a big picture. Having a dataset, even open, without the whole process from the collection to the moment it is publicly available is usually not enough.

- **Data corruption**: at any stage of the collection, processing and usage, the data may be partly corrupted. It may be hard to determine where and how the data has been corrupted even if the data are open.

- **Biased data**: from the collection process itself to the sanitization choices, bias may be introduced. Having access to open data is no help for building better models and algorithms if data are biased from the beginning.

- **Missing unexpected patterns or learning wrong patterns**: for some reasons, regime change might occur in the data and be or not learnt by a model. How to know if this change is valid or is the result of a problem somewhere between the data collection (e.g. some sensors are not working or being recalibrated) and the data processing (e.g. a bug in the software used to sanitize the data) \textit{without} expert knowledge? Some points may also be outliers for good reasons (e.g. improbable event that \textit{eventually} occurs, often referred as a \textit{black swan}) or bad reasons (e.g. error in processing the data, problem in collecting the data)? In the first case, the models \textit{must} take into account those data, while in the second case, it should be discarded. Open data cannot help, except for very obvious cases.

For those reasons, the datasets presented in this paper are accompanied with the full creation process, carefully documented.

One of the prominent domains of application for Deep Learning is computer vision. In this area, it is relatively easy to obtain new data, even if the process of manually labelling training data may be laborious. Techniques like Data Augmentation allow to generate artificially new data by slightly modifying existing examples \cite{dyk2001}. For instance, for hand-written recognition, one may add some small perturbations or apply transformations.
to an existing example, such as rotation, zoom, gaussian noise, etc. Those techniques are efficient at providing useful new examples but rely on an implicit assumption: the solution’s behavior changes continuously with the initial conditions. In other words, slightly modifying the picture of a 8 by a small rotation or distortion still results in a 8. However, in many other fields, a small change in the data may result in a totally different outcome such that one cannot use Data Augmentation to artificially grow her dataset. In general, the fields where Data Augmentation is not possible are more complex, requires more information to process or require a sophisticated or conscious reasoning before being able to give an answer. Anyone can recognize a cat from a horse without processing any additional data than the picture itself, without elaborating a complex and explicit reasoning. Conversely, deciding if someone is guilty w.r.t. some available information and the current legal environment is not as natural as recognizing a cat, even from the best legal experts.

We would like to draw the attention on the fact that, it is not because those fields are more complex for humans that nowadays artificial intelligence techniques cannot perform better than humans: medical diagnosis is a complex field requiring expertise and explicit reasoning, however humans are regularly beaten by the machine (Tiwari et al. (2016); Yu et al. (2016); Patel et al. (2016)). This said, in many complex fields, data augmentation techniques cannot be used, access to the data may be difficult, the data itself can be limited and, when open, the data are provided already curated without access to the curation process. ECHR-OD project has been created with those considerations in mind.

2 ECHR-OD presentation

2.1 Context and previous work

For some years and in several areas of the Law, some "quantitative" approaches have been developed, based on the use of more or less explicit mathematical models. With the availability of massive data, those trends have been accentuated and brand new opportunities are emerging at a sustained pace. Among the stakes of those studies, one can mention a better understanding of the legal system and the consequences some decisions on the economy, but also the possibility to decrease the mass of litigations in a context of cost rationalization (see Quemy (2017) for a survey on legal analytics methods).

The Supreme Court of the United States (SCOTUS) has been widely studied, notably through the SCOTUS database (Katz et al. (2017); Martin et al. (2004); Guimerà and Sales-Pardo (2011)). This database is composed of structured information about every case since the creation of the court. The opinions and other related textual documents also have been studied specifically for SCOTUS (Islam et al. (2016); Lauderdale and Clark (2014); Sim et al. (2014)). Conversely, very little if no similar work has been done in Europe. As far as

http://scdb.wustl.edu/
we know, the only predictive model was only using the textual information
(Aletras et al. (2016)) while more structured information is publicly available on HUDOC
(3). The authors of Aletras et al. (2016) did provide their data but it suffers from few problems. First, their data is far from being exhaustive: 3 articles considered (3, 6 and 8) with respectively 250, 80 and 254 cases per article. For many data-driven algorithms, this might be too little for a correct training. Secondly, despite the data processing method is clearly stated (top 2000 n-grams extraction for some parts of the judgments such as “Procedure”, “Facts”, etc.), the authors provided only the final Bag-of-Words and TF-IDF representations. As stated in the introduction, if anything bad happens during this process, but only the final result is available, it may be impossible to determine if the approach is unsuitable or if the data are simply bad. More concretely, we noticed that many cases were described by an empty vector which probably resulted in pessimistic results for the authors of Aletras et al. (2016).

2.2 Project presentation and philosophy

ECHR-OD project aims at providing an exhaustive and high-quality database and datasets based on the European Court of Human Rights documents available on HUDOC. It appears important to us 1) to draw the attention of researchers on this domain with large consequences on the society, 2) to provide a similar database for the European Union as it already exists in the United States, notably because the law systems are different in both sides of the Atlantic. The project is composed of four components:

1. Main website: http://aquemy.info/echr-od
2. Download mirror: https://osf.io/s2rhg/
3. Creation process: https://github.com/aquemy/ECHR-OD_process
4. Website sources: https://github.com/aquemy/ECHR-OD_website

ECHR-OD is guided by three core values: reusability, quality and availability. To reach those objectives,

- each version of the datasets is carefully versioned and publicly available, including the intermediate files,
- the integrality of the process and files produced is careful documented,
- the scripts to retrieve the raw documents and build the datasets from scratch are open-source and carefully versioned to maximize reproducibility and trust,
- no data is manipulated by hand at any stage of the creation process.

The datasets are available under Open Database License (ODbL) which guarantees the rights to copy, distribute and use the database, to produce works from the database and to modify, transform and build upon the

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3 https://hudoc.echr.coe.int/eng
4 Summary: https://opendatacommons.org/licenses/odbl/summary/
5 Full-text: https://opendatacommons.org/licenses/odbl/1.0/
database. The creation process scripts and website sources are provided under MIT Licence.

3 Datasets description

3.1 Classification problem

In machine learning, the problem of classification consists in finding a mapping from an input vector space $\mathcal{X}$ to a discrete decision space $\mathcal{Y}$ using a set of examples. The binary classification problem is a special case of the multiclass such that $\mathcal{Y}$ has only two elements, while in multilabel classification, each element of $\mathcal{X}$ can have several labels. It is often viewed as an approximation problem s.t. we want to find an estimator $\hat{J}$ of an unknown mapping $J$ available only through a sample called training set. A training set $(\mathbf{X}, \mathbf{y})$ consists of $N$ input vectors $\mathbf{X} = \{\mathbf{x}_1, ..., \mathbf{x}_N\}$ and their associated correct class $\mathbf{y} = \{J(\mathbf{x}_i) + \epsilon\}_{i=1}^N$, possibly distorted by some noise $\epsilon$. Let $\mathcal{J}(\mathcal{X}, \mathcal{Y})$ be the class of mappings from $\mathcal{X}$ to $\mathcal{Y}$. Solving an instance of the classification problem consists in minimizing the classification error:

$$J^* = \arg \min_{J \in \mathcal{J}(\mathcal{X}, \mathcal{Y})} \sum_{\mathbf{x} \in \mathcal{X}} I_{\{J(\mathbf{x}) \neq \hat{J}(\mathbf{x})\}}$$  \hspace{1cm} (1)

3.2 Datasets flavors and representation

From the HUDOC database and judgment files, we created several datasets for three variants of the classification problem: binary classification, multiclass classification and multilabel classification. There are 11 datasets for binary, 1 for multiclass and 1 for multilabel classification.

Each dataset comes in different flavours based on descriptive features and Bag-of-Words and TF-IDF representations:

1. **Descriptive features**: structured features retrieved from HUDOC or deduced from the judgment document,
2. **Bag-of-Words representation**: based on the top 5000 tokens (normalized $n$-grams for $n \in \{1, 2, 3, 4\}$),
3. **TF-IDF representation**: idem but with a TF-IDF transformation to weight the tokens,
4. **Descriptive features + Bag-of-Words**: combination of both sets of features,
5. **Descriptive features + TF-IDF**: combination of both sets of features.

Those different representations exist to study the respective importance of descriptive and textual features in the predictive models build upon the datasets. This also allows comparing between methods working only with BoW and methods only with descriptive features.
Table 1 Datasets description for binary classification.

| Article  | # cases | min #features | max #features | avg #features | prevalence |
|----------|---------|--------------|--------------|--------------|------------|
| Article 1 | 932     | 131          | 2834         | 1177.83      | 0.93       |
| Article 10 | 534     | 49           | 3440         | 1654.06      | 0.75       |
| Article 11 | 191     | 293          | 3758         | 1308.37      | 0.62       |
| Article 13 | 1078    | 44           | 2908         | 1380.37      | 0.62       |
| Article 2  | 594     | 44           | 3501         | 1805.66      | 0.84       |
| Article 3  | 1724    | 160          | 3871         | 1491.67      | 0.86       |
| Article 34 | 136     | 490          | 3168         | 1726.78      | 0.32       |
| Article 5  | 1613    | 200          | 3656         | 1430.26      | 0.64       |
| Article 6  | 5668    | 46           | 3168         | 1095.43      | 0.82       |
| Article 8  | 1060    | 179          | 3685         | 1449.55      | 0.66       |
| Article p1 | 1200    | 266          | 2692         | 1166.88      | 0.89       |

The columns min, max, avf #features indicate the minimal, maximal and average number of features in the dataset cases for the representation “descriptive features + Bag-of-Words representation”.

For binary classification, the label corresponds to a violation or no violation of a specific article. Each of the 11 datasets corresponds to a specific article. We kept only the articles such that there are at least 100 cases with a clear output (see Section Filtering Cases for additional details) without consideration for the prevalence. Notice that a same case can appear in two datasets if it has in his conclusion two elements about a different article. A basic description of those datasets is given by Table 1.

For multiclass, there are a total of 22 different classes (the number of different articles multiplied by two possible decisions: violation or no violation). To create the multiclass dataset, we aggregate the different binary classification dataset. To do so, we removed the cases that appeared in several datasets. We did not simply merge the binary classification datasets for the remaining cases. The processing part consisting in the creation of the BoW and TF-IDF representations is based on the 5000 most frequent n-grams among the corpus of judgments (see Section Normalizing documents for additional details). As the most frequent n-gram changes when adding more judgments, the BoW representation in the multiclass and multilabel corpus is different from the BoW representation in the respective binary classification corpus. The descriptive features are not changed.

For multilabel classification, there are 22 different labels and the main difference with the multiclass is that there is no need to remove cases that appear in multiple binary classification datasets. The labels are simply stacked. Due to this difference, the corpus is different from the multiclass’ one and again, the BoW and TF-IDF representations are different. Table 3 summarizes the dataset composition, Figures 2 and 3 shows the label repartition among the multiclass and multilabel datasets, and Figure 4 provides the histogram of label numbers and cases per label.

The final format to encode the case information is close to LIBSVM format. Each couple (variable, value) is encoded by <variable_id>:<value_id>
Table 2 Dataset description for the multiclass dataset.

| Article | # cases | violation | no-violation |
|---------|---------|-----------|--------------|
| 1       | 360     | 321 (0.030) | 39 (0.004) |
| 10      | 468     | 359 (0.034) | 109 (0.010) |
| 11      | 153     | 132 (0.012) | 21 (0.002)  |
| 13      | 55      | 46 (0.004)  | 7 (0.001)   |
| 2       | 559     | 478 (0.045) | 81 (0.008)  |
| 3       | 1420    | 1235 (0.115) | 185 (0.017) |
| 34      | 26      | 23 (0.002)  | 3 (0.000)   |
| 5       | 1125    | 988 (0.092) | 137 (0.013) |
| 6       | 5250    | 4821 (0.450)| 429 (0.040) |
| 8       | 790     | 573 (0.053)| 217 (0.020) |
| p1      | 509     | 438 (0.041)| 71 (0.007)  |

For each article is indicated the number of cases, the number of cases labeled as violated and not violated with in parenthesis the prevalence w.r.t. the whole dataset.

Table 3 Dataset description for the multilabel dataset.

| Article | # cases | violation | no-violation |
|---------|---------|-----------|--------------|
| 1       | 951     | 882 (0.082) | 69 (0.006)  |
| 10      | 560     | 418 (0.039) | 142 (0.013) |
| 11      | 213     | 180 (0.017) | 33 (0.003)  |
| 13      | 1090    | 997 (0.093) | 93 (0.009)  |
| 2       | 1124    | 1017 (0.095)| 107 (0.010) |
| 3       | 2573    | 2205 (0.214)| 278 (0.026) |
| 34      | 136     | 87 (0.008)  | 49 (0.005)  |
| 5       | 2292    | 2081 (0.194)| 211 (0.020) |
| 6       | 6891    | 6152 (0.574)| 739 (0.069) |
| 8       | 1289    | 940 (0.088)| 349 (0.033) |
| p1      | 1301    | 1120 (0.105)| 181 (0.017) |

For each article is indicated the number of cases, the number of cases labeled as violated and not violated with in parenthesis the prevalence w.r.t. the whole dataset.

Table 4 Files contained in a dataset.

| File                  | Description                                      |
|-----------------------|--------------------------------------------------|
| descriptive.txt       | Descriptive features only.                       |
| BoW.txt               | Bag-of-Word representation only.                 |
| TF_IDF.txt            | TF-IDF representation only.                      |
| descriptive+BoW.txt   | Descriptive features and Bag-of-Words.           |
| descriptive+TF_IDF.txt| Descriptive features and TF-IDF.                 |
| outcomes.txt          | Contain the labels of the datasets.              |
| features_descriptive.json | Mapping between feature and numerical id.     |
| features_text.json    | Mapping between n-grams and numerical id.        |
| outcomes_variables.json | Mapping between labels and numerical id.       |
| variables_descriptive.json | Mapping between descriptive variable and numerical id. |
| statistics_datasets.json | Contain some statistics about the dataset.    |

with the specificity that the <value_id> is not encoded per variable but globally. For instance, 0:7201 corresponds to variable itemid=001-170361. The
encoding for the variables can be found in `variables_descriptive.json` and the encoding for the couples (variable, value) in `features_descriptive.json`. The format for the mapping `features_descriptive.json` is "<variable>=<value>":<id> or "<variable> has <value>":<id> if the variable is a set of elements. For instance, the variable `parties` has two elements and is encoded by 19. Having "BASYUK" in the parties of a case is encoded by "parties has BASYUK": 109712 and thus, the case description contains 19:109712 and 19:X where X is the id for the second party. As the id is global, having the variable id in prefix is redundant. Notice that it has at least two advantages. First, there is no need to look in the global dictionary and parse the corresponding key.
to know the encoded variable. Second, some algorithms might want a pair (variable, value) (e.g. Decision Tree) while others can work with global tokens (e.g. Neural Network). Finally, it makes it easier to re-encode the cases with a specific encoder (e.g. binary, Helmert, Backward Difference, etc.).

Regarding the Bag-of-Words representation, each n-gram is turned into a variable such that when a case judgment contains a specific token, the final representation contains <token_id>:<occurrences>. For instance, assume the 2-gram "find_guilty" is encoded by 128210 and appears 5 times in a judgment, the case description will contain 128210:5. For TF-IDF representation, <occurrences> is replaced by the specific weight for this token in the document given the whole dataset.

4 Creation process

In this section, we describe in detail the dataset generation process from scratch. The datasets are based on the raw documents and information available publicly in the HUDOC database. The process is broken down into several steps as illustrated by Figure 5:

1. get_cases_info.py: Retrieve the list and basic information about cases from HUDOC,
2. filter_cases.py: Remove unwanted, inconsistent, ambiguous or difficult-to-process cases,
3. get_documents.py: Download the judgment documents for the filtered list of cases,
4. preprocess_documents.py: Analyse the raw judgments to construct a JSON nested structures representing the paragraphs,
5. **process_documents.py**: Normalize the documents and generate a Bag-of-Words and TF-IDF representation,

6. **generate_datasets.py**: Combine all the information to generate several datasets.

![Fig. 5 ECHR-OD datasets creation process.](image)

The integrality of this process is wrapped into a script `build.py`. This script has some parameters such as the output folder name but also the number of tokens to take into consideration during the generation of Bag-of-Words representation. This allows anyone to generate slightly modified versions of the datasets and to experiment with them. To ease the contribution and small tests, there exist some flags to update the output produced by one of the steps as well as an option to force overwriting the previously obtained results. However, for the datasets releases, we impose as requirement to generate successfully the integrality of the build process from an empty folder to ensure the output files are up-to-date with HUDOC and the last version of the scripts.
4.1 Retrieving cases

Using HUDOC API, basic information about all entries are retrieved and saved in JSON files. Those entries contain several keys that are listed on top of the script `get_case_info.py`. Among them can be found the case name, the language used, or the conclusion in natural language. See Appendix 5 for an example of a case description.

4.2 Filtering cases

To ensure the quality and usability of the datasets, we filter the cases as follows:

1. We keep only cases in english,
2. We keep only cases with a judgment document,
3. We remove the cases without an attached judgment document,
4. We keep only the cases with a clear conclusion (i.e. containing at least one occurrence of “(no) violation”),
5. We remove a specific list of cases hard to process (three cases for this version of the datasets).

During this step, we also parse and format some raw information: the parties are extracted from the case title and many raw strings are broken down into lists. In particular, the string listing the articles discussed in a case are turned into a list and the conclusion string into a slightly more complex JSON object. For instance, the string

Violation of Art. 6-1; No violation of P1-1; Pecuniary damage - claim dismissed; Non-pecuniary damage - financial award

becomes the list of elements described in Appendix 5.

In general, each item in the conclusion can have the following elements:

1. article: number of the concerned article if applicable,
2. details: list of additional information (paragraph or aspect of the article),
3. element: part of the raw string describing the item,
4. mentions: diverse mentions (quantifier s.a. 'moderate', country,...),
5. type: violation, no violation or other.

Some representative examples are provided by Appendix 5.

Finally, on top of saving the case information in a JSON file, we output a JSON file for each unique article with at least 100 associated cases. This constant is a parameter of the script and can thus be modified for additional experimentations.

Additionally, some basic statistics about the attributes are generated, e.g. the cardinality of the domain and the density (i.e. the cardinality over the total number of cases). For instance, the attribute itemid is unique and thus, as expected, its density is 1:

```json
"itemid": {  
  "cardinal": 12075,  
  "density": 1.0  
}
```
In comparison, the field article (raw string containing a list of articles discussed in a case) and article (its parsed and formatted counterpart) score respectively 25% and 1% for the density. This illustrates the interest of our processing method: using the raw string, the article attribute is far more unique that it should be. In reality, there are about 130 different values that are really used across the datasets.

```
"articles": {
    "cardinal": 3104,
    "density": 0.2570600414078675
}

"article": {
    "cardinal": 131,
    "density": 0.010848861283643893
}
```

4.3 Getting documents

During this phase, we only download the judgment documents in Microsoft Word format using HUDOC API.

4.4 Preprocessing documents

The preprocessing step consists in parsing the MS Word document to extract additional information and create a tree structure of the judgment file. It outputs two files for each case:

1. `<case_id>.parsed.json`: same JSON document as produced by `filter_cases.py` with additional information.
2. `<case_id>.text_without_conclusion.txt`: full judgment text without the conclusion. It is meant to be used for creating the BoW and TF-IDF representations.

To the previous information, we add the field `decision_body` with the list of persons involved into the decision, including their role. See Appendix 5 for an example.

The most importation addition to the case info is the tree representation of the whole judgment document under the field `content`. The content is described in an ordered list where each element has two fields: 1) `content` to describe the element (paragraph text or title) and 2) `elements` that represents a list of sub-elements. For a better understanding, see the example in Appendix 5. This representation eases the identification of some specific sections or paragraphs.
4.5 Normalizing documents

During this step, the documents <case_id>_text_without_conclusion.txt are normalized as follows:

- Tokenization,
- Stopwords removal,
- Part-of-Speech tagging followed by a lemmatization,
- n-gram generation for $n \in \{1, 2, 3, 4\}$,

The output files are named <case_id>_normalized.txt.

4.6 Processing documents

This step uses Gensim (ˇReh˚uˇrek and Sojka (2010)) to construct a dictionary of the 5000 most common tokens based on the normalized documents (the dictionary is created per dataset) and outputs the Bag-of-Words and TF-IDF representations for each document. The naming convention is <case_id>_bow.txt and <case_id>_tfidf.txt. Additionally, feature_to_id.dict and dictionary.dict contain the mapping between tokens and id, respectively in JSON and in a compressed format used by Gensim. The number of tokens to use is a parameter of the script.

4.7 Generating datasets

The final step consists in producing the dataset and related files. See Table 4 for the list of output files. The feature id of the BoW and TF-IDF parts are not the same as those obtained during the processing phase. More precisely, they are shifted by the number of descriptive features.

We remove the cases with no clear output. For instance, it is possible to have a violation of a certain aspect of a given article but no violation of another aspect of the same article. In the future, we will consider a lower label level than the article.

5 Conclusion

In this paper, we introduced the European Court of Human Right Open Data project consisting in multiple datasets for several variants of the classification problems. The datasets come in different flavors (descriptive features, Bag-of-Word representation, TF-IDF) and are based on the real-life data directly retrieved from the HUDOC database. In total, 13 datasets are provided for the first release. We argued that providing the final data are not enough to ensure quality and trust. In addition, there are always some opinionated choices in the representation, such as the number of tokens, the value of $n$ for the $n$-grams calculation or the weighting schema in the TF-IDF transformation. As
a remedy, we provide the whole process of dataset construction from scratch. The datasets will be iteratively corrected and updated along with the ECHR new judgments. The datasets are carefully versioned to reach a compromise between the need to keep the data up-to-date (as needed by legal practitioners or algorithms in production) and to have the same version of data to compare between paper results.

In the future, we plan to add additional enrichments (e.g. entity extraction from the judgments), new datasets with fine-grain labels and new datasets for different problems (e.g. structured prediction). We hope to offer a web platform such that anyone can tune the different dataset hyperparameters to generate its own flavor: a sort of Dataset as a Service.

Last but not least, we encourage all researchers to explore the data, generate new datasets for various problems and submit their contributions to the project.

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Supplementary Material

S1 Appendix. Example of raw information returned by HUDOC.

S2 Appendix. Structure of a conclusion element.

S3 Appendix. Example of conclusion elements.

S4 Appendix. Example of decision body information.

S5 Appendix. Tree structure of a parsed judgment file.