Language-Agnostic Website Embedding and Classification

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Abstract
Currently, publicly available models for website classification do not offer an embedding method and have limited support for languages beyond English. We release a dataset with more than 1M websites in 92 languages with relative labels collected from Curlie, the largest multilingual crowdsourced Web directory. The dataset contains 14 categories aligned across languages. Alongside it, we introduce Homepage2Vec, a machine-learned pre-trained model for classifying and embedding websites based on their homepage in a language-agnostic way. Homepage2Vec, thanks to its feature set (textual content, metadata tags, and visual attributes) and recent progress in natural language representation, is language-independent by design and can generate embeddings representation. We show that Homepage2Vec correctly classifies websites with a macro-averaged F1-score of 0.90, with stable performance across low- as well as high-resource languages. Feature analysis shows that a small subset of efficiently computable features suffices to achieve high performance even with limited computational resources. We make publicly available the curated Curlie dataset aligned across languages, the pre-trained Homepage2Vec model, and libraries at: https://github.com/epfl-dlab/homepage2vec

Introduction
Website classification plays an essential role for numerous purposes, from Web analysis to search engine design to Web security. However, despite the importance both for the research community and industry, the common practice is to rely on a few proprietary solutions, typically offered with a commercial license and with limited support for languages beyond English. The goal of this paper is to release a multilingual labeled dataset collected from Curlie and to introduce Homepage2Vec, a pre-trained model that supports the classification and embedding of websites starting from their homepage. Curlie is the largest human-edited directory of the Web, which acts as the successor to the now-defunct DMOZ and is freely available online. We focus our effort on collecting data and developing a language-agnostic model by selecting and combining features that do not depend on a website’s language. This aspect is particularly important when dealing with content from the Web: e.g., a study based on the top 10M websites estimated that in 2020 around 40% of Web content was not in English. Recent progress in NLP and the release of pre-trained cross-lingual language models enable us to revisit website classification and representation in new ways. Combined with visual properties and HTML metadata, novel NLP-based features offer an abstraction for representing Web pages without language dependency. Homepage2Vec is based on a jointly trained neural network that returns the individual probability that a website belongs to 14 classes obtained from Curlie. Learning the individual per-class probability with a single network makes the model flexible to support at the same time binary relevance and embedding.

With this article, we release a curated version of the Curlie dataset, the labels aligned to English, the pre-trained model, and a Python library to embed and classify any website. All the resources are available at: https://github.com/epfl-dlab/homepage2vec

Related work
Our work is related to different topics spanning from the classification of websites to representing textual and visual features in a language-independent setup.

Website classification. Since the very beginning of the world wide web development, website classification has emerged as a hard problem. Unlike other classification tasks where the documents come from the same source (i.e., forum messages, tweets, news feeds), websites are extremely diverse in terms of content, language, authorship, visual style, and intended audience. Early approaches, which relied on the manual creation of taxonomies, keyword lists, and custom classification methods (Chakrabarti, Dom, and Indyk 1998; Chukuri et al. 1997), were later superseded by machine learning methods, which used both textual and contextual features (Dumas and Chen 2000; Sun, Lim, and Ng 2002; Calado et al. 2003, 2006; Cai et al. 2003; Kan and Tim 2005; Rajalakshmi and Aravindan 2011; Shawon et al. 2018; Kan 2004; Baykan et al. 2009). Other researchers proposed to extend the extraction of features beyond the properties of the current document by exploring the neighboring pages (Zhu et al. 2016). This strategy has the advantage of aiding the classifier with more contextual information when the page is minimal in content and not very informative. In a similar spirit to our work, researchers in the past also explored the effectiveness of visual features in classifying Web pages (de Boer et al. 2010). More recently, researchers have started to explore deep architectures based

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on LSTM (Deng, Du, and Shen 2020), GRU (Du, Han, and Zhao 2018), and BERT (Gupta and Bhatia 2021) applied to textual and HTML features. Although, unlike us, focusing only on a single language or a subset of very popular websites, these directions have shown how performance can be improved with the help of more complex models.

**Multilingual text representation.** While structural and visual signals can bring additional information, the textual signal remains the of paramount importance in describing a website. A traditional method used in the past was to encode a document by a vector of weights proportional to the frequencies of terms (TF-IDF). A breakthrough in the field of textual representation was word2vec (Mikolov et al. 2013), which offers a convenient method to obtain embedding vectors for words. Another step forward was the development of BERT (Devlin et al. 2019), a transformer-based neural network that has been effectively adapted to the multilingual setting (e.g., mBERT, LaBSE (Feng et al. 2020), XLM (Lample and Conneau 2019), XLM-R (Conneau et al. 2020)). For instance, XLM-R has been shown to offer language-independent embeddings with performance comparable to monolingual models (Conneau et al. 2020).

**Embedding of visual features.** Our use of visual features for website classification leverages recent advances in deep learning–based computer vision. Here, models are generally composed of a sequence of convolutional layers for feature extraction, followed by one dense layer that acts as a classifier (Krizhevsky, Sutskever, and Hinton 2012; He et al. 2015). This scheme has the advantage that the second-to-last layer can be viewed as a low-dimensional visual embedding of the input, which can serve as a feature for downstream tasks, such as website classification in our case.

**Curated Curlie dataset**

*Curlie* is an online community-edited Web directory, which serves as the successor to the now-defunct DMOZ. In total, Curlie contains more than 3M URLs in 92 languages, labeled in a hierarchical ontology of categories. The contributing community classified the websites according to 15 top-level categories: ART, BUSINESS, COMPUTERS, GAMES, HEALTH, HOME, NEWS, RECREATION, REFERENCES, REGIONAL, SCIENCE, SHOPPING, SOCIETY, SPORTS, and KIDS AND TEENS. These categories are then organized into a hierarchical taxonomy with a high level of granularity. We collected the Curlie dataset and the content of the websites in April 2021 and pre-processed it in the following way: we retained only homepages recognized by the empty URL path, dropped duplicates, discarded non-accessible URLs, and assigned the respective top-level labels as categorical classes (labels). In our dataset, we exclude the top-level label REGIONAL because it is a location-based classification that conveys little information about the content of the website. This filtering leaves us 1.05M websites with a topic-based label. Since the assigned labels are language-specific, together with the labels full hierarchy path and original HTML content, we release a dataset containing the mapping between the different taxonomy levels across all languages. The datasets are encoded in JSON, and Table 1 summarises their structure.

The distribution of top-level classes (mapped to English) and languages is shown in Fig. 1a and Fig. 1b. The majority of the websites are associated with BUSINESS, SOCIETY, and ARTS, while the categories with fewer instances are about NEWS and KIDS AND TEENS. English is the most represented language followed by German and Japanese. Although each page may, in principle, have an arbitrary number of category labels, at the top level, the data is mostly single-labeled, with only 2.1% of samples appearing in two or more taxonomy trees of 14 top-level classes.

### Homepage2Vec

To show the potential of Curlie dataset and provide a useful resource to the research community, we developed Homepage2Vec, a model trained on multi-language Curlie that can classify and embed any website. This section describes the set of features used, the model architecture, and the training setup.

### Features

We identify four types of features: domain name–based, textual, visual, HTML metadata–based. We concatenate all these features (described in detail next) into a single high-dimensional vector to have a complete representation of the different aspects of the website. All features are extracted from the homepage of a website only. This is important in practice, as it means websites need not be crawled in full; only the homepage URL needs to be known and downloaded.

#### Textual content

Webpage text is the most straightforward feature to use in website classification. We start by extract-
ing the page’s plain-text content, splitting it into sentences, and generating sentence embeddings with XLM-R \cite{conneau2020unsupervised}. Then, we compute the average of these vectors to obtain a single vector of 768 dimensions representing the document. Since the generation of these vectors is computationally expensive, we use only the first $N = 100$ sentences. We selected this threshold on a development set using the elbow method applied to the model’s performance at different levels of $N$.

**Visual.** Visual components can play an important role in understanding the topic of a website. Humans looking at a website written in an unknown language can still often guess the type of website. Indeed, the document’s layout, colors, and images can give strong hints about its content. To operationalize this intuition, we use Selenium WebDriver\footnote{https://www.selenium.dev/} to collect screenshots of the Web pages by simulating the visible portion in a browser window of $1,920 \times 1,080$ pixels, which is standard for a computer screen. In this step, we faced the challenge of removing the modal windows typically used to display cookie information, often covering the main content. We tackle this problem with a heuristic-based approach by removing div tags whose text contains or id contains the substrings $\text{popup, modal, or cookie}$ before capturing screenshots. We used the obtained images to generate a visual embedding with a pre-trained ResNet-18 model \cite{he2015deep}, following the pipeline described by He et al. \cite{he2015deep}, i.e., splitting the screenshots into five crops (center plus four corners), feeding each crop to the model, and averaging the outputs.

**Top-level domain.** Some top-level domains (TLD) such as .edu or .biz can offer a good hint about the website’s content. For example, a typical use case for the first case is university websites, whereas the second is commonly associated with business activities. Following this intuition, we collected from Common Crawl\footnote{https://commoncrawl.org/} a large-scale sample of the Web, the 19 most frequent TLDs: \texttt{.com, .org, .net, .info, .xyz, .club, .biz, .top, .edu, .online, .pro, .site, .vip, .icu, .buzz, .app, .asia, .gov, .space}, excluding the country code TLD (ccTLD) because they indicate geographic origin, not website content. We represent this feature with a one-hot encoding vector of 19 dimensions.

**Domain name.** We preprocess the domain names by removing the TLD and separator symbols ("." and "_"), and splitting domain parts at the "_" symbol. When present, we drop the common prefix www. After these steps, we embed the individual tokens with XLM-R and average the vectors.

**Title, description, keywords.** Website owners are encouraged to add meta information about the content of their pages to facilitate the indexing of search engines. Since fields such as title, description, and keywords are typically carefully curated and very informative, we extract them from the HTML of the Web page and represent them as three feature vectors via XLM-R.

**Links.** A website’s homepage often contains links to other internal pages with explicit reference to its content. For example, by looking at the first five links of a university website, we may find EN, About, Education, Research, and Innovation, which can be used as an indication of its academic content. We extract all the URL paths of the links on the homepage, split them into words, feed the $K = 50$ most frequent words to XLM-R, and average their outputs. This approach is motivated by the fact that some parts of the link URL paths are very frequent on the page, which implicitly gives more importance to the left component of the URL path. Also, it allows keeping the complexity under control, as the number of links for some websites can be very large. Similar to the case of the textual features, we selected the best value of $K$ with the elbow method on a development set.

**Metatags.** As in the case of description and keywords, the owners of the websites can add additional metatags to their pages to improve indexing. An example includes the tag rating, which is mainly associated with adult websites. We consider the 30 most frequent metatags from a sample of the Common Crawl and represent their presence with a hot-one encoding vector.

**Model architecture**

The model (Fig. \ref{fig:model}) is a single neural network with an input layer of dimensionality 5,169 to accommodate all features and an output layer of size 14. The network’s output represents the probability of (independently) belonging to each of the 14 categories (samples may have multiple labels). The network has two fully connected hidden layers of dimensions 1,000 and 100, respectively. We use rectified linear
We decrease the learning rate by a factor of 0.1 if the loss on a held-out set of 1000 samples decreases for 10 consecutive epochs. Finally, we stop the training when the learning rate reaches the value of $10^{-8}$.

### Training

The training loss is defined by the average of the binary cross-entropy for each class. We tackle the imbalance between positive and negative samples by adapting the loss function to add a reweighting factor to the positive cases. For each positive training sample, the weight is given by the ratio between negative and positives samples in its class. We train on mini-batches of size 128 using the Adam optimizer and a starting learning rate of $10^{-4}$. We decrease the learning rate by a factor of 0.1 if the loss on a held-out set of 1000 samples decreases for 10 consecutive epochs. Finally, we stop the training when the learning rate reaches the value of $10^{-8}$.

### Evaluation

#### Website embedding

We train and calibrate Homepage2Vec to predict the independent probability for each class, but using a single model across classes gives the additional advantage of supporting the generation of embedding vectors. The embedding is a 100-dimensional vector, available as the output of the last hidden layer of the neural network. These vectors can be used to cluster websites, measure their distance, or study the topical distribution in a subset of the Web. Fig. 7 shows how the embedding obtained respects the Curlie labels and how it groups nearby similar websites.

#### Website classification

**Balanced setup.** First, we evaluate the model by considering the probability returned by each category’s independent binary classifier. We assess the individual performance in a balanced setup by balancing positive and negative samples on the testing set for each class. Performance by class is shown in Fig. 4. The macro-averaged precision is 0.920, recall 0.886, F1-score 0.902, AUC/ROC 0.963. Thanks to language-independent features, the model has stable performances across multiple languages, as shown in Fig. 5.

**Unbalanced setup.** Next, we evaluate the model on the entire testing set with its original, unbalanced class distribution to have a sense of the performances for real-world applications. Precision–recall curves for all classes are shown in Fig. 6a. The results show that the evaluation of the model on unbalanced data partially reduces performance, giving a macro-average precision of 0.771, recall 0.549, F1-score 0.634, AUC/ROC 0.964. The most impacted classes are the ones with only a few samples, like KIDS AND TEENS (cf. Fig. 1a). Two reasons primarily cause this outcome: first, discarding samples from very small classes such as KIDS AND TEENS (around 1% of the dataset) is harder than from large classes such as BUSINESS (27%); and second, the testing set has missing labels. We will explore this issue and give more reassuring details in the following section.

Because we simulate a balanced distribution during training, the output of the classifiers must be calibrated to reflect the class priors in the testing set. For this purpose, Saerens et al. (Saerens, Latrine, and Decaestecker 2002) proposed a simple procedure for transforming the output values of a classifier. In the case of binary classifiers trained on a balanced distribution, the calibrated prediction for sample $i$ and class $k$ is $\hat{s}_{ik} = s_{ik}/(s_{ik} + p_k(1-s_{ik}))$, where $s_{ik}$ is the original, uncalibrated prediction and $p_k$ is the ratio of negative vs. positive samples for class $k$ (computed on the randomly sampled training set before balancing). We assess calibration via the calibration plots of Fig. 6b. The output probabilities were first grouped in bins of equal width, and then, for each bin, the fraction of positive samples is plotted against the mean value of the bin. We conclude that our model is well calibrated, as the resulting curve (orange) lies close to the diagonal. The thresholds of 0.5 marked in Fig. 6a were determined on the calibrated model.

### Feature importance

Some of the proposed features require deep models, such as XLM-R or ResNet-18, and are computationally heavy to obtain. We want to assess the performances on the classification task if we are forced to use a limited subset of features, for example in the case of restricted resources. We first rank the features according to their complexity, where we take into account both the access (online vs offline) and the computational complexity. We incrementally add the features starting from the least complex one, re-train the model and evaluate on a balanced setup. The architecture stays fixed, only the input dimension varies to match the incremented features. The results are shown in Fig. 6c. We observe that efficient performances can be achieved without using the heaviest features. This is a useful property that can be profitable for real-world applications.

### Evaluation on human ground truth

Curlie, like its predecessor DMOZ, is an excellent source of labeled websites, but it is not a perfect ground truth. Due to its human-curated nature, Curlie cannot be considered to be
exhaustively labeled. Contributors add websites to a predetermined taxonomy, and in many cases, they select only one among all the relevant categories.

Manual inspection revealed that relevant labels are frequently missing, leading to high precision but imperfect recall of the human ground truth. Even the evaluation of a perfect predictive model trained and tested on the Curlie data would obtain imperfect performance when evaluated on perfectly labeled data. By manually inspecting the misclassified websites, we observed that the model tends to correctly assign a high probability to all relevant classes, even when the label is missing in the testing sample.

We further explored this observation by enriching the labels via a crowdsourced task on Amazon Mechanical Turk. We collected binary labels for all 14 categories for 807 websites. The interface showed the website content, description, title, and workers answered a series of binary questions. These websites originally had a total of 836 labels, according to Curlie (1.04 on average), but received 2,088 labels (2.59 on average) from crowd workers, a 2.5x increase. This lack of complete labels is consistent across categories, significantly impacting categories with few websites. For instance, while in the dataset only 11 websites were originally labeled as KIDS AND TEENS, crowd workers assigned this label to 76 websites.

The overall performance computed on the labels obtained via human annotation brings the macro-averaged precision of the unbalanced set from 0.734 to 0.873. These results suggest that the low precision on some classes (Fig. 6a) is not so much a shortcoming of Homepage2Vec, and that the model can be used to enrich the original data.

**Library**

With the dataset and pre-trained models, we release a Python library that supports classification and embedding starting from the URL of the website. The library offers automatic content fetching, as well processing pre-fetched content, and allows users to embed it in any project with little effort. It supports classification both with and without visual features to adapt the task to the available resources. The library and usage instructions are publicly available at: [https://github.com/epfl-dlab/homepage2vec](https://github.com/epfl-dlab/homepage2vec)

**Conclusion**

With this article, we release a large-scale dataset with labeled websites in 92 languages obtained from Curlie. To support the research community, we used this data to develop Homepage2Vec, a pre-trained model for classifying and embedding websites. Due to its language-agnostic features, the model performs well for low- as well as high-resource languages. Future work to further improve the model performance includes the exploration of additional features. For example, visual features can be extended to represent the stylistic aspects of the page: i.e., websites for kids may look aesthetically very different than business homepages. Similarly, metadata features could be exploited further to represent structural properties like links network and the DOM organization. We look forward to seeing these tools applied in building and analyzing an increasingly polyglot World Wide Web.

**Ethical considerations.** Curlie moderators make sure the dataset does not contain websites promoting individual products, marketing schemes, or illegal content. Additionally, since we collected only the websites of unrestricted categories, adult content is also excluded from our dataset.

Finally, in this work, we relied on the work of human annotators on the Amazon Mechanical Turk platform. Our workers compensation was in line with ethical guidelines for AMT [Salehi et al. 2015, Whiting, Hugh, and Bernstein 2019].

[https://curlie.org/docs/en/guidelines/include.html](https://curlie.org/docs/en/guidelines/include.html)
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