LanideNN: Multilingual Language Identification on Character Window

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Abstract

In language identification, a common first step in natural language processing, we want to automatically determine the language of some input text. Monolingual language identification assumes that the given document is written in one language. In multilingual language identification, the document is usually in two or three languages and we just want their names. We aim one step further and propose a method for textual language identification where languages can change arbitrarily and the goal is to identify the spans of each of the languages.

Our method is based on Bidirectional Recurrent Neural Networks and it performs well in monolingual and multilingual language identification tasks on six datasets covering 131 languages. The method keeps the accuracy also for short documents and across domains, so it is ideal for off-the-shelf use without preparation of training data.

1 Introduction

The World Wide Web is an ever growing source of textual data, especially data generated by web users. As more people get access to the web, more languages and dialects start to appear and need to be processed. In order to be able to use such data for further natural language processing (NLP) tasks, we need to know in which languages they were written. Language identification is thus a key component for both building various NLP resources from the web and also for running many web services.

Techniques of language identification can rely on handcrafted rules, usually of high precision but low coverage, or data-driven methods that learn to identify languages based on sample texts of sufficient quantity.

In this paper, we present a data-driven method for language identification based on bidirectional recurrent neural networks called *LanideNN* (language identification by neural networks, NN). The model is trained on character sliding window of input texts with the goal of assigning a language to each character. We show that the method is applicable for a large number of languages and across text domains without any adaptation and that it performs well in monolingual (one language per document) as well as multilingual (a few languages per document) language identification tasks. Also, the performance does not drop with shorter texts.

The paper is structured as follows. In Section 2, we briefly review current approaches to language identification. Section 3 introduces our method, including the technical details of the neural network architecture. For the training of our model, we collect and manually clean a new dataset, as described in Section 4. The model is evaluated on standard test sets for monolingual (Section 5) as well as multilingual (Section 6) language identification. Section 7 illustrates the behavior of our method in the motivating setting: identifying languages in short texts. We conclude and summarize our plans in Section 8.

2 Related Work

Of the many possible approaches to language identification Hughes et al. (2006), character n-gram statistics are among the most popular ones. Cavnar et al. (1994) were probably the first; they used the 300 most frequent character n-grams (with n ranging from 1 to 5, as is also typically used in other works). All the n-gram-based approaches differ primarily in the calculation of the distance between the n-gram profile of the training and test text (Selamat, 2011; Yang and Liang, 2010), or by using additional features on top of the n-gram profiles (Padma et al., 2009; Carter et al., 2013). One of the fairly robust definitions of the distance (or similarity) was proposed by Choong et al. (2009) who simply check the proportion of n-gram types seen in the tested document of the most frequent n-gram types extracted from training documents for each language. The highest-scoring language is then returned.

Hughes et al. (2006) mention a number of freely available tools at that time. Since then, one aspect of the tools became also important: the number of languages covered.

The language identification tool CLD2[1] by Google detects 80 languages and uses a Naive Bayes classifier, treating specifically unambiguous scripts such as Greek and using either character unigrams (Han and similar scripts) or fourgrams.

Another popular tool is Langid.py by Lui and Baldwin (2012), covering 97 languages out of the box. Langid.py relies on Naive Bayes classifier with a multinominal event model and mixture of byte n-grams for training. The tool includes tokenization and fast feature extraction using Aho-Corasick string matching.

To our knowledge, and also according to the survey by Garg et al. (2014), neural networks have not been used often for language identification so far. One exception is Al-Dubaee et al. (2010), who combine a feed-forward network classifier with wavelet transforms of feature vectors to identify English and Arabic from the Unicode representation of words, sentences or whole documents. The benefit of NN in this setting is not very clear to us because English and Arabic can be distinguished by the script. During writing of this paper, we have found a new pre-print paper (Jaech et al., 2016) which handles language identification with NN. Specifically, they employ Convolutional Neural Networks followed by Recurrent Neural Networks. Their approach labels text on the word level, which is problematic in languages without clear word delimiters. In comparison with our model, they need to pre-process the data and break long words into smaller chunks, whereas we simply use text without any preprocessing.

In practice, several tools are often used at once, with some form of majority voting. For example, Twitter internal language detector uses their in-house tool along with CLD2 and Langid.py, and this triple agreement is reported to make less than 1 % of errors.[2]

Multilingual language identification, i.e. identification of the set of languages used in a document, is a less common task, explored e.g. by Lui et al. (2014) who use a generative mixture model on multilingual documents and establish the relative proportion of languages used. Character n-grams again serve as features, selected by information gain.

Solorio et al. (2014) organized a shared task in language identification at the word level. This matches our aim, but the task included only four language pairs and more importantly, the dataset was collected from Twitter and for copyright reasons it is not available any more.

3 Proposed Method

The method we propose is designed for short text without relying on document boundaries. Obviously, if documents are known and if they can be assumed to be monolingual, this additional knowledge should not be neglected. For the long term, we however aim at a streamlined processing of noisy data genuinely appearing in multilingual environments. For instance, our method could support the study of switching of languages ("code switching") in e-mails or other forms of conversation, or to analyse various online media such as Twitter, see e.g. Montes-Alcalá (2007) or Solorio et al. (2014).

Our model takes source letters as input and provides a language label for each of them. Whenever we need to recognize the language of a document, we take the language assigned by our model to the majority of letters.

The goal of attributing a language tag to the smallest text units is one of the reasons why we decided to use neural networks and designed the model to provide a prediction at every time step without much overhead.

In the rest of this section, we explain the architecture and training methods of the model.

[1]`https://github.com/CLD2Owners/cld2`

[2]`https://blog.twitter.com/2015/evaluating-language-identification-performance`

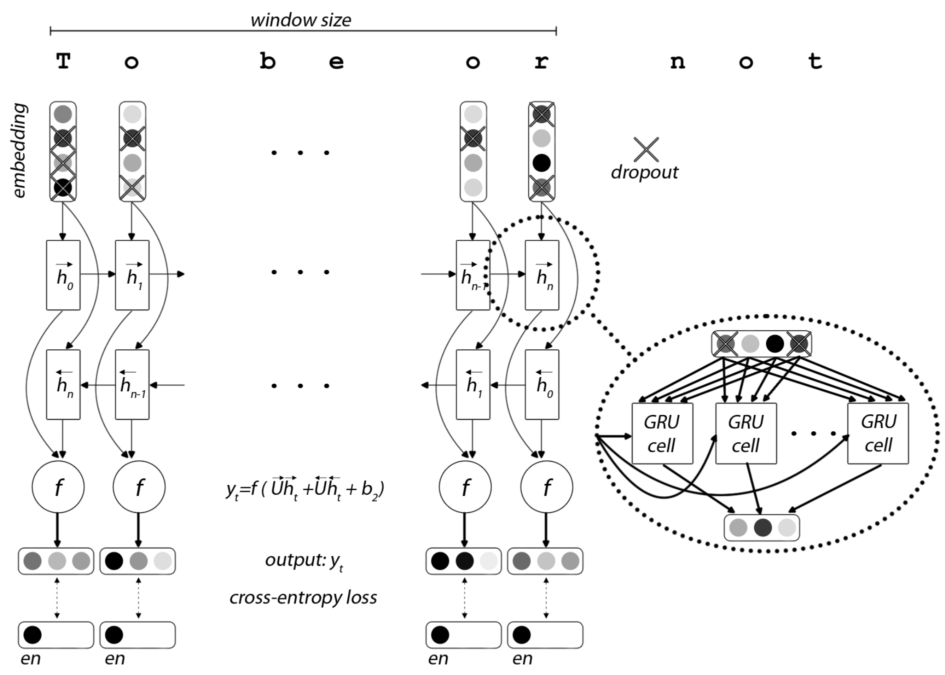


Figure 1: Illustration of our model LanideNN.

3.1 Bidirectional Recurrent Neural Networks

A recurrent neural network *RNN* (Elman, 1990) is a variant of neural networks with recurrent connections in time. In principle, the history information available to an RNN is not limited (subject to a processing window, if used), so the network can condition its output on features from a long distance. The LSTM, one of the variants of RNN, makes it particularly suitable for sequential prediction tasks with arbitrary time dependencies, as shown by Hochreiter and Schmidhuber (1997).

In this work, we use the Elman-type network, where the hidden layer h_t at a time step t is computed based on the current input layer x_t and the previous state of the hidden layer h_{t-1}. The output y_t is then derived from the h_t by applying the softmax function f. More formally:

$$h_t = \tanh\left(Wx_t + Vh_{t-1} + b_1\right) \quad (1)$$

$$y_t = f\left(Uh_t + b_2\right) \quad (2)$$

where U, V and W are connection weights to be computed in training time and bias vectors b_1 and b_2.

With the above definition, the RNN has access only to information preceding the current position in the text. In our setting, the rest of the text (in a fixed-size window) is available, so we want to allow the model to use also future information, i.e. letters following the currently examined one. We therefore define a second RNN which reads the input from the end to the beginning, changing the definition to:

$$\overrightarrow{h}_t = \tanh\left(\overrightarrow{W}x_t + \overrightarrow{V}\overrightarrow{h}_{t-1} + \overrightarrow{b}_1\right) \quad (3)$$

$$\overleftarrow{h}_t = \tanh\left(\overleftarrow{W}x_t + \overleftarrow{V}\overleftarrow{h}_{t+1} + \overleftarrow{b}_1\right) \quad (4)$$

$$y_t = f\left(\overrightarrow{U}\overrightarrow{h}_t + \overleftarrow{U}\overleftarrow{h}_t + b_2\right) \quad (5)$$

where the left and right arrows indicate the direction of network.

The simple unit with only tanh non-linearity is difficult to train and therefore we have selected the Gated Recurrent Unit (GRU), recently proposed by Cho et al. (2014), as a replacement. We also considered Long Short-Term Memory cells (LSTM) but they achieved slightly worse results in our setting. This changes equations (1), (3) and (4). The proper equations for the GRU can be found in Cho et al. (2014).

The model outputs a probability distribution over all language tags. In order to determine the language of a character, we take the tag with the maximum value.

The complete model is sketched in Figure 1.

3.2 Training, Embeddings and Dropout

We train the model using the first-order stochastic gradient descent method Adam (Kingma and Ba, 2015). Our training criterion is the cross-entropy loss function[3].

We represent each Unicode character using an e-dimensional real valued vector, analogously to word embeddings of Collobert et al. (2011). The character embeddings are initialized randomly and are trained together with the rest of the network.

To prevent overfitting, we use dropout (Srivastava et al., 2014) during model training on the character embedding layer[4]. The key idea is to randomly drop (avoid updating of) connections. This prevents neurons from co-adapting too much, i.e. starting to depend on outputs of other neurons too much, which is a typical symptom of overfitting to training data.

3.3 Model Design

Our model operates on a window of 200 characters of input text, i.e. individual letters, encoded in Unicode. Each character corresponds to one time step of the BiRNN in the respective direction, see Figure 1. The model classifies each character separately, but quickly learns to classify neighbouring characters with the same label.

For documents longer than the window size, we simply move to the next window without any overlap. The last window (or the only window if the document were too short) is filled with a padding character, so the network always works on windows of the same size.

We set e, the size of the embedding layer, to 200. The BiRNN uses a single hidden layer of 500 GRU cells for each direction.

The main model was trained for over 530,000 steps (each step is the processing of one batch of inputs) on a single core of the GeForce GTX Titan Z GPU. The training took around 5 days. The stopping criterion for the training was the error on a development set.

4 Training Data

Our goal is to develop an off-the-shelf language recognizer, with no need for retraining by the user and covering as many languages as possible. Finding suitable training data is thus an important part of the endeavour.

[3]We set the learning rate to 0.0001 and train with the batch size of 64 windows.

[4]We set the dropout to the probability of 0.5 as customary.

afr, amh, ara, arg, asm, ast, aze, bak, bcl, bel, ben, ber, bpy, bre, bul, cat, ceb, ces, che, chv, cos, cym, dan, deu, div, ekk, ell, eng, est, eus, fas, fin, fra, fry, gla, gle, glg, gom, gsw, guj, hat, heb, hif, hin, hrv, hsb, hun, hye, ido, ilo, ina, ind, isl, ita, jav, jpn, kal, kan, kas, kat, kaz, kir, kor, kur, lat, lav, lim, lit, ltz, lug, lus, mal, mar, min, mkd, mlg, mlt, mon, mri, msa, nds, nep, new, nld, nno, nor, nso, oci, ori, oss, pam, pan, pms, pnb, pol, por, pus, roh, ron, rus, sah, scn, sin, slk, slv, sna, som, spa, sqi, srp, sun, swa, swe, tam, tat, tel, tgk, tgl, tha, tur, uig, ukr, urd, uzb, vec, vie, vol, wln, yid, zho, zul

Figure 2: The 131 languages (and HTML) recognized by our system.

We start from Wikipedia, as crawled and converted to a large multilingual corpus W2C by Majliš and Žabokrtský (2012). W2C contains 106 languages but we had to exclude a few of them[5] because they contained too little non-repeating text.

We then focussed on finding corpora with at least some languages not covered by the already collected data. Those corpora were added whole, including languages that we already had, to improve the variety of our collection. We made use of the following ones:

Tatoeba[6] is a collection of simple sentences for language learners. Tatoeba contains sentences in 307 languages, but for most languages it has only a few hundred sentences.

Leipzig corpora collection (Quasthoff et al., 2006) covers 220 languages with newspaper text and other various texts collected from the web.

EMILLE (Baker et al., 2002) contains texts in 14 Indian languages and English.

Haitian Creole training data (Callison-Burch et al., 2011) were prepared by the organizers of WMT11 shared task on machine translation of SMS messages sent to an emergency hotline in the aftermath of the 2010 Haitian earthquake. We used only the official documents from the training data, not the actual SMS messages because they contained a lot of noise.

[5]Specifically, HAT, IDO, MGL, MRI, VOL, as identified by ISO language codes.

[6]`http://tatoeba.org/`

Test Set	Documents	Languages	Encoding	Document Length (bytes)	Avg. # characters
EuroGov	1500	10	1	17460.5 ± 39353.4	17037.3
TCL	3174	60	12	2623.2 ± 3751.9	1686.1
Wikipedia	4963	67	1	1480.8 ± 4063.9	1314.2

Table 1: Summary of testsets for monolingual language identification.

Additionally, we wanted our tool to distinguish HTML tags in the data, since they are the most frequent markup that needs to be separated from the processed data. Therefore, we have downloaded several Github projects in HTML and collected all strings enclosed with angle brackets, as a rather permissive approximation of HTML tags. We have dropped tags which were too long and we put each tag on a separate line. We have not deduplicated them for the training set.

The cleanup of the collected data was mostly manual. We deduplicated each of the sources by dropping identical lines, regardless of what lines correspond to in the individual sources (words, phrases, sentences or even paragraphs). We inspected data files for individual languages and removed lines containing English for languages not using Latin script. We also removed Cyrilic characters from a few languages that should not contain them. This was done mostly in W2C corpora.

For the final dataset, we mixed all sources for a given language at the line level, keeping only languages with more than 500k characters in total. Since the resources for some languages were huge, we decided to set an upper bound on the number of characters per language. In order to roughly reflect the distribution of languages in the world, we divided languages into three groups based on the number speakers of the language according to Wikipedia. The first group were languages with more than 75M speakers, the second with more than 10M speakers and the third group contained the rest. For the first group, we allowed at most 10M characters in the training set, the second group was capped at 5M characters and the third group was allowed only 1M characters per language at most.[7]

In total, our final training set includes 131 + 1 (HTML) languages, see Figure 2.

We divide the corpus into non-overlapping training, development and test sections. We released the test set [8] but the training part cannot be publicly released because of the restrictive permissions of some of the sources used. The test section is limited to short text. It contains 100 lines for each of the 131 languages (HTML is not included), with the average line length of 142.3 characters.

Each line of the dataset starts with an ISO-3 label of the language presented on that line. All lines were shuffled.

For training and testing, the language labels as well as all line breaks must be ignored, otherwise the model could learn to set language boundaries at the new line character. After dropping all line breaks, we obtain a multilingual text.

This way, we simulate a multilingual text and our algorithm has to learn to identify language boundaries without relying on any particular symbol. We are aware of the fact that the original segmentation of the corpora affects where these language switches are expected, and this will mostly correspond to sentence boundaries.

5 Monolingual Language Identification

Most of related research is focused on monolingual language identification, i.e. recognizing the single language of an input document.

We compare our method in this setting with several other algorithms on the dataset presented by Baldwin and Lui (2010). The dataset consists of 3 different test sets, each containing a different number of languages, styles and document lengths collected from different sources, see Table 1 for details:

EuroGov contains texts in Western European languages from European government resources.

TCL was extracted by the Thai Computational Linguistics Laboratory in 2005 from online news sources and the test set also contains multiple file encodings. Since our method assumes Unicode input, we converted TCL to Unicode encoding.

[7]Higher-quality sources such as Tatoeba are generally smaller and since we mixed the sources by interleaving their lines, these smaller sources were likely included in full.

[8]https://ufal.mff.cuni.cz/tom-kocmi/lanidenn

System	Trained on	Supported languages	EuroGov	TCL	Wikipedia
LangDetect*	Wikipedia	53	**.992**[9]	.818	.867
TextCat*	TextCat Dataset	75	.941	.605	.706
CLD*	unknown	64	.983	.732	.831
Langid.py*	Lui and Baldwin (2011)	97	.987	.904	**.913**
Langid.py	Lui and Baldwin (2011)	97	.987	.931	**.913**
CLD2	unknown	83	.979	.837	.854
Our model	Our dataset	**136**	.977	**.954**	.893

Table 2: Results of monolingual language identification on the Baldwin and Lui (2010) test set. Entries marked with "*" are accuracies reported by Lui and Baldwin (2012), the rest are our measurements.

Wikipedia are texts collected from a Wikipedia dump.

Table 2 summarizes the accuracies of several algorithms on the three test sets. For some algorithms, we report values as presented by Lui and Baldwin (2012) without re-running[9]. We re-ran the Langid.py as the best algorithm out of them, and got the same results except for the TCL testset, where we got better results than reported by Lui and Baldwin (2012). After a discussion with the authors, we believe the re-run benefited from the conversion of all texts to Unicode.

We compare our method with two top language recognizers, Langid.py and CLD2. Our model is trained on more languages and we do not restrict it to the languages included in the test set, so we may be losing on detailed dialect labels.

Despite the considerably higher number of languages covered, our model performs reasonably close to the competitors on EuroGov and Wikipedia and best on TCL.

5.1 Short-Text Language Identification

In order to demonstrate the ability of our method to identify language of very short texts such as tweets, search queries or user messages, we wanted to use an existing corpus, such as the one released by Twitter.[10] Unfortunately, the corpus contains only references to the actual tweets and most of them are no longer available. We thus have to rely on our own test set, as described in Section 4.

Results on short texts are reported in Table 3. The two other systems, Langid.py and CLD2 cover fewer languages and they were trained on texts unrelated to our collection of data. It is therefore not surprising that they perform much worse when averaged over all languages.

System	All languages	Common languages
Langid.py	.567	.912
CLD2	.545	.891
Our model	**.950**	**.955**

Table 3: Results on our test set for short texts. The first column shows accuracy over all 131 languages and the second column shows accuracy over languages that all systems have in common.

ind↔msa	64	ekk↔est	36	bak↔tat	28
hrv↔srp	17	glg↔por	17	nno↔nor	16
ast↔spa	15	fas↔pus	13	ces↔slk	13
hrv↔slv	10	dan↔nor	10	nep↔new	8
aze↔tur	7	mar↔new	6	ceb↔tgl	6
cat↔spa	6	arg↔spa	6	fra↔oci	5

Table 6: Most frequent confusions on our test set.

For a fairer comparison, we report also accuracies on a restricted version of the test set that included only languages supported by all the three tested tools. Both our competitors are meant to be generally applicable, so they should (and do) perform quite well. Our system nevertheless outperforms them, reaching the accuracy of 95.5. Arguably, we can be benefitting from having trained on (different) texts from the same sources as this test set.

Table 6 lists the most frequent misclassifications of our model on our test set (unordered language pairs) of the 13100 items in the test set. The most common error is confusing Indonesian with Modern Standard Arabic, which indicates some noise in our training data rather than difficulty of separating these two languages. The following pairs are expected: Standard Estonian (ekk) vs. Estonian (est, a macro language which includes Standard Estonian), Bashkir vs. Tatar, Croatian vs. Serbian, Asturian vs. Spanish, ...

Finally, our model is trained to distinguish also

[9]We should mention that LangDetect used EuroGov as a validation set, so its score on this test set is not reliable.

[10]`https://blog.twitter.com/2015/evaluating-language-identification-performance`

System	Training set	P_M	R_M	F_M	P_μ	R_μ	$\mathbf{F}_\mu$
VRL (2010) *	ALTW2010	.497	.467	.464	.833	.826	.829
ALTW2010 winner *	ALTW2010	.718	.703	.699	.932	.931	.932
SEGLANG *	ALTW2010 - mono	.801	**.810**	.784	.866	.946	.905
LINGUINI *	ALTW2010 - mono	.616	.535	.513	.713	.688	.700
Lui et al. (2014) *	ALTW2010 - mono	.753	.771	.748	.945	.922	.933
Lui et al. (2014) our retrain	ALTW2010 - mono	.768	.716	.724	**.968**	.896	.931
Our model	ALTW2010 - mono	**.819**	.764	.779	.966	**.964**	**.965**
Our model	Our dataset	.709	.714	.695	.941	.941	.941

Table 4: Results of multilingual language identification on the ALTW2010 test set. * As reported by Lui et al. (2014)

System	P_M	R_M	F_M	P_μ	R_μ	$\mathbf{F}_\mu$
SEGLANG *	.809	**.975**	.875	.771	**.975**	.861
LINGUINI *	.853	.772	.802	.838	.774	.805
Lui et al. (2014) *	.962	.954	.957	**.963**	.955	.959
Lui et al. (2014) our retrain	.962	.963	.961	**.963**	.964	.963
Our model trained on WikipediaMulti	.962	.974	**.966**	.954	.974	**.964**
Our model trained on our dataset	.774	.778	.774	.949	.972	.961
Our model trained on our dataset, restricted	**.966**	.973	**.966**	.956	.973	**.964**

Table 5: Results of multilingual language identification on the WikipediaMulti test set. * As reported by Lui et al. (2014)

HTML as one additional language. We did not include HTML in our test corpus but to satisfy the requests of one of our reviewers, we checked the performance on our development corpus: only one Portuguese and one Yakut segment was classified as HTML and none of the 100 HTML segments were misclassified.

6 Multilingual Language Identification

In multilingual language identification, systems are expected to report the set of languages used in each input document. The evaluation criterion is thus macro- (M) or micro- (μ) averaged precision (P), recall (R) or F-measure (F).[11]

We evaluate our model on two existing test sets for multilingual identification, ALTW2010 shared task and WikipediaMulti. We are mainly interested in the performance of our general model, trained on all our training data, on these test sets. But since both test sets come with training data, we also retrain our model to test its in-domain performance. We limit the training of these specific models to 140,000 training steps for ALTW2010 and 75,000 steps for WikiMulti, keeping other settings identical to the main model. Each training step amounts to the processing of 64 batches of 200 letters of input. The number of steps for both tasks was established by testing the error on the development parts of the datasets.

To interpret the character-level predictions by our model for multilingual identification, we used the ALTW2010 development data to empirically set the threshold: if a language is predicted for more than 3 % of characters in the document, it is considered as one of the languages of the document.

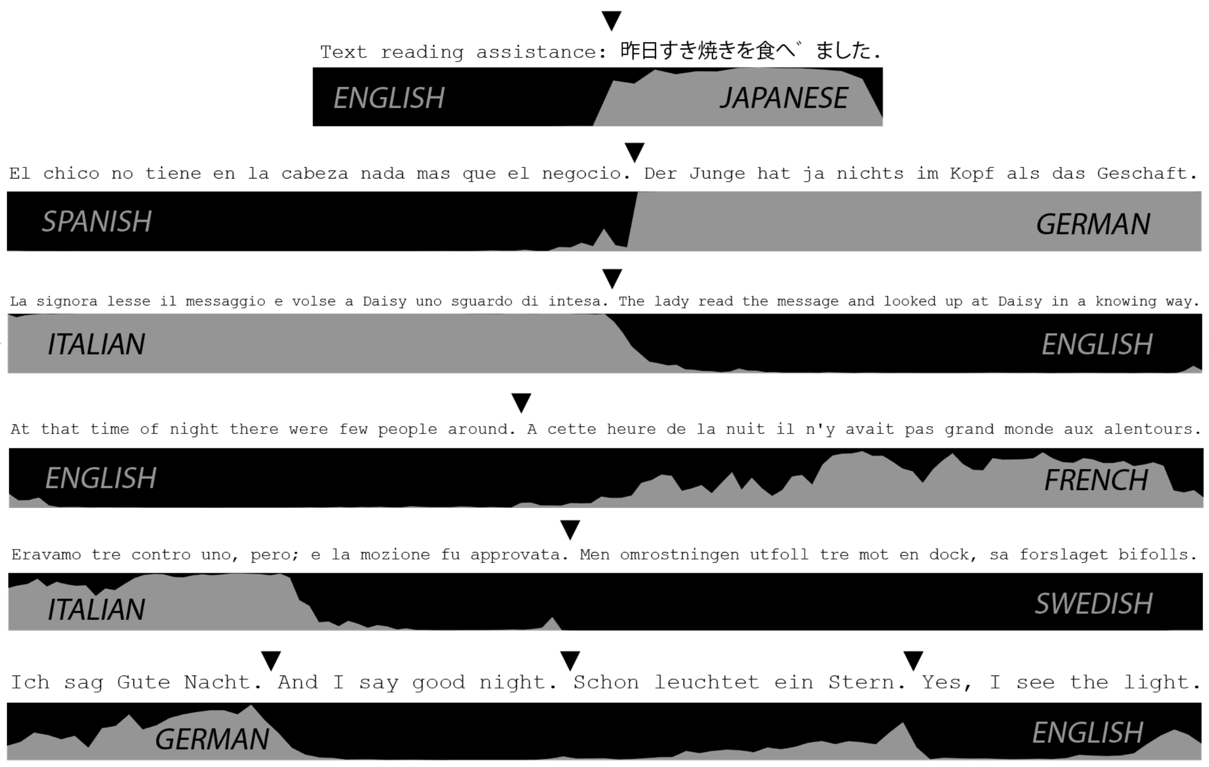
6.1 ALTW 2010 Shared Task

ALTW 2010 shared task (VRL, 2010) provided 10000 bilingual documents divided as follows: 8000 training, 1000 development and 1000 test documents.

The results on the 1000 test documents are in Table 4. For algorithms SEGLANG and LINGUINI, we only reproduce the results reported by Lui et al. (2014). We use the system by Lui et al. (2014) as a proxy for the comparison: we retrain their system and obtain results similar to those reported by the original authors. The differences are probably due to the Gibbs sampling used in their approach.

Some of the reported methods rely on the fact that the documents in the dataset are bilingual. Other methods, including ours, simply break the bilingual documents into the individual languages and train on this simplified training set. We indicate this by stating "ALTW2010 - mono" in Table 4.

[11]Note that for comparability with results reported in other works, macro-averaged F-score is calculated as average over individual F-scores instead of the harmonic mean of P_M and R_M. F_M can thus fall out of the range between P_M and R_M.



Text reading assistance: 昨日すき焼きを食へ゛ました.

El chico no tiene en la cabeza nada mas que el negocio. Der Junge hat ja nichts im Kopf als das Geschaft.

La signora lesse il messaggio e volse a Daisy uno sguardo di intesa. The lady read the message and looked up at Daisy in a knowing way.

At that time of night there were few people around. A cette heure de la nuit il n'y avait pas grand monde aux alentours.

Eravamo tre contro uno, pero; e la mozione fu approvata. Men omrostningen utfoll tre mot en dock, sa forslaget bifolls.

Ich sag Gute Nacht. And I say good night. Schon leuchtet ein Stern. Yes, I see the light.

Figure 3: Illustration of text partitioning. The black triangles indicate true boundaries of languages. The black part shows probability with which the language written in gray is detected and the gray part shows complement for the second language, since in this setup we restricted our model to use only the two languages in question. The misclassification of Italian and German as English in the last two examples may reflect increased noise in our English training data.

The main criterion of the ALTW2010 shared task was to maximize the micro-averaged F-score ($\mathbf{F}_\mu$). We see that our model trained on the ALTW2010 data outperforms all other models in this criterion ($\mathbf{F}_\mu$ of .965) and so does our non-adapted version, reaching $\mathbf{F}_\mu$ of .941.

6.2 WikipediaMulti

WikipediaMulti (Lui et al., 2014) is a dataset of artificially prepared multilingual documents, mixed from monolingual Wikipedia articles from 44 languages. Each of the artificial documents contains texts in $1 \leq k \leq 5$ randomly selected languages. The average document length is 5500 bytes. The training set consists of 5000 monolingual documents, the development set consists of 5000 multilingual documents and test set consists of 1000 documents for each value of k.

Table 5 shows that our model performs well, both when trained on the provided data and when trained on our training corpus. The model trained on our dataset performs slightly worse in $\mathbf{F}_\mu$, but if we simply prevent it from predicting languages not present in the test set, the score gets on par with the adapted version, see the line labelled “restricted” in Table 5.

7 Text Partitioning

Figure 3 illustrates the behaviour of our model on text with mixed languages. We have selected very short (50–130 characters) and challenging segments where the languages mostly share the same script. Finding the boundary between languages written in different scripts is quite easy, as illustrated by the first example.

Only too late, we discovered that King and Abney (2013) provide a test set for word-level identification for 30 languages. We thus have to leave the evaluation of our model on this dataset for future.

8 Conclusion

We have developed a language identification algorithm based on bidirectional recurrent neural networks. The approach is designed for identifying languages on a short texts, allowing to detect code switching including switches to formal markup languages like HTML.

We collected a dataset and trained our model to recognize considerably more languages than other state-of-the-art tools. Our algorithm and the trained model is provided for academic and personal use.[12]

Since there is no established dataset for the novel setting of text partitioning by language, we evaluated our model in several common tasks (monolingual and multilingual language identification for long and short texts) which were previously handled by separate algorithms. Our approach performs well, improving over the state of the art in several cases.

A number of things are planned: (1) improving the implementation, especially the speed of application of a trained model, (2) further extending the set of covered languages and possibly including more artificial or programming languages (e.g. JavaScript, PHP) or common formal notations (URLs, hashtags), (3) evaluating our method on the dataset by King and Abney (2013), possibly extending this dataset to include more languages, (4) training and testing the model on noisy texts like Tweets or forum posts, and (5) experimenting with other network architectures and approaches, possibly also training the model on bytes instead of Unicode characters.

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