Sentence Boundary Detection for French with Subword-Level Information Vectors and Convolutional Neural Networks

Carlos-Emiliano González-Gallardo, Juan-Manuel Torres-Moreno

1LIA, Université d’Avignon et des Pays de Vaucluse
2École Polytechnique de Montréal

carlos-emiliano.gonzalez-gallardo@alumni.univ-avignon.fr, juan-manuel.torres@univ-avignon.fr

Abstract

In this work we tackle the problem of sentence boundary detection applied to French as a binary classification task (“sentence boundary” or “not sentence boundary”). We combine convolutional neural networks with subword-level information vectors, which are word embedding representations learned from Wikipedia that take advantage of the words morphology; so each word is represented as a bag of their character n-grams. We decide to use a big written dataset (French Gigaword) instead of standard size transcriptions to train and evaluate the proposed architectures with the intention of using the trained models in posterior real life ASR transcriptions.

Three different architectures are tested showing similar results: general accuracy for all models overpasses 0.96. All three models have good F1 scores reaching values over 0.97 regarding the “not sentence boundary” class. However, the “sentence boundary” class reflects lower scores decreasing the F1 metric to 0.778 for one of the models.

Using subword-level information vectors seem to be very effective leading to conclude that the morphology of words encoded in the embeddings representations behave like pixels in an image making feasible the use of convolutional neural network architectures. Index Terms: Convolutional Neural Networks, Automatic Speech Recognition, Machine Learning, Sentence Boundary Detection

1. Introduction

Multimedia resources provide nowadays a big amount of information that automatic speech recognition (ASR) systems are capable to transcribe in a very feasible manner. Modern ASR systems like the ones described in [1] and [2] obtain very low Word Error Rate (WER) for different French sources (17.10% and 12.50% respectively), leading to very accurate transcriptions that could be used in further natural language processing (NLP) tasks.

Some NLP tasks like part-of-speech tagging, automatic text summarization, machine translation, question answering and semantic parsing are useful to process, analyze and extract important information from ASR transcriptions in an automatic way [3][4]. For this to be accomplished a minimal syntactic structure is required but ASR transcriptions don’t carry syntactic structure and sentences boundaries in ASR transcriptions are inexistent.

Sentence Boundary Detection (SBD), also called punctuation prediction, aims to restore or predict the punctuation in transcripts. State of the art show that research has been done for different languages like Arabic, German, Estonian, Portuguese and French [3][4][5][6][9]; nevertheless English is the most common one [3][4][5][10][11]. In this paper we focus on French, nevertheless, the proposed architectures and the concepts behind can be used to other languages.

There exist two different types of features in SBD and the use of each type depends of their availability and the methods that will be used. Acoustic features rely on the audio signal and the possible information that could be extracted like pauses, word duration, pitch and energy information [3][12][13]. Lexical features by contrast, depend on transcriptions made manually or by ASR systems, dealing to textual features like bag of words, word n-grams and word embeddings [3][4][6][7].

Conditional random fields classifiers have been used in [4][10] to predict different punctuation marks like comma, period, question and exclamation marks. In [3], adaptive boosting was used to combine many weak learning algorithms to produce an accurate classifier also for period, comma and question marks. Hand-made contextual rules and partial decision tree algorithms were considered in [7] to find sentence boundaries in Tunisian Arabic. In [6], a hierarchical phrase-based translation approach was implemented to treat the sentence boundary detection task as a translation one.

Deep neural networks were used with word embeddings in [3] to predict commas, periods and questions marks. Three different models were presented: the first one considered a standard fully connected deep neural network while the other two implemented convolutional neural network architectures. Concerning the word embeddings, 50-dimensional pre-trained GloVe word vectors were chosen to perform experiments; this embeddings use a distinct vector representation for each word. Che et al. recovered the standard fully connected deep neural network architecture presented in [4], then an acoustic model was introduced in a 2-stage joint decision scheme to predict the sentence boundary positions.

Following the scheme described in [3], we aboard the SBD as a binary classification task. The objective is to predict the associated label of a word $w_i$ inside a context window of $m$ words using only lexical features. Audio sources are normally used to train and test SBD models which are not reused for later applications. We want to create models that can be reutilized in further SBD work, so we approach the topic in a different manner using a big written dataset.

2. Model Description

2.1. Subword-Level Information Vectors

Subword-Level Information (SLI) vectors [14] are word embedding representations based on the continuos skip-gram model...
2.2. Convolutional Neural Network Models

Convolutional Neural Networks (CNN) are a type of Deep Neural Network (DNN) in which certain hidden layers behave like filters that share their parameters across space.

The most straightforward application for CNN is image processing, showing outstanding results [10,20]. However they are useful for a variety of NLP tasks like sentiment analysis and question classification [21]; part-of-speech and named entity tagging, semantic similarity and chunking [22]; sentence boundary detection [23] and word recognition [24] between others.

The input layer of a CNN is represented by a \( m \times n \) matrix where each cell \( c_{ij} \) may correspond to an image’s pixel in image processing. For our purpose this matrix represents the relation between a window of \( m \) words and their corresponding \( n \) dimensional SLI vectors. The hidden layers inside CNN consist of an arrange of convolutional, pooling and fully connected layers blocks.

2.2.1. Text matrix representation

Given the intrinsic relation between the components of SLI vectors, we think it is feasible to make an extrapolation to the existing relation between adjacent pixels of an image. This way the \( m \times n \) matrix of the input layer will be formed by the context window in (1) where \( w_i \) is the word for which we want to get the prediction. The columns of the matrix will be represented by each one of \( n \) components of their corresponding SLI vectors.

\[
\{w_{i-(m-1)/2}, \ldots, w_{i-1}, w_i, w_{i+1}, \ldots, w_{i+(m-1)/2}\}
\]  

2.2.2. CNN-A

The hidden architecture of the first model (Figure 1 (CNN-A)) is based on a model presented in [3]. It is composed of three convolutional layers (A_conv-1, A_conv-2 and A_conv-3), all three with valid padding and stride value of one. A_conv-1 has a 2x4-shape kernel and 64 output filters, A_conv-2 has a 2-shape kernel and 128 output filters and A_conv-3 has a 1x49-shape kernel and 128 output filters. After A_conv-1, a max pooling layer (A_max_pool) with 2x3-shape kernel and stride of 1x3 is applied. After A_conv-2, a dropout layer (A_dropout) is added. The output of all convolutional max pooling and fully connected layers are in function of RELU activations.

2.2.3. CNN-B

In our second model (Figure 1 (CNN-B)) we tried to reduce the complexity generated by the three convolution layers of CNN-A. For this model there are only two convolutional layers (B_conv-1 and B_conv-2), both with valid padding and stride value of one. B_conv-1 has a 3-shape kernel and 32 output filters while B_conv-2 has a 2-shape kernel and 64 output filters. To downsample and centralize the attention of the CNN in the middle word of the window, a max pooling layer (B_max_pool) with 2x3-shape kernel and stride of 1x3 is applied after B_conv-2. The final part of the CNN is formed by 3 fully connected layers (B_f_c-1, B_f_c-2 and B_f_c-3) with 2048, 4096 and 2048 neurons each and a dropout layer (B_dropout) attached to B_f_c-3. The output of all convolutional max pooling and fully connected layers are in function of RELU activations.

2.2.4. CNN-C

Finally, in our third model (Figure 1 (CNN-C)) we simplified the fully connected layers of CNN-B. The convolutional and max pool layers (C_conv-1, C_conv-2 and C_max_pool) are the same than in CNN-B. For this model, only one fully connected layer of 2048 neurons is present (C_f_c-1) which is attached to a dropout layer (C_dropout). The output of all convolutional max pooling and fully connected layers are in function of RELU activations.

3. Experimental Evaluation

3.1. Dataset

SBD experimentation datasets normally rely on automatic or manual transcriptions to train and test the proposed systems [3,6,11]. As shown in Table 1 the amount of tokens is, in average 21.25k, which only 2.5k (12.48%) correspond to any punctuation mark.

In order to reuse the proposed architectures and trained models for real life ASR transcriptions and further NLP applications we opted for a big written dataset. It consists of one section of the French Gigaword First Edition [3] (GW_alg) created...
Table 1: Oral datasets.

| Dataset      | tokens | punctuation | percentage |
|--------------|--------|-------------|------------|
| WSJ          | 51k    | 5k          | 9.8%       |
| TED Ref      | 17k    | 2k          | 11.8%      |
| TED ASR      | 17k    | 2k          | 11.8%      |
| Dict         | 25k    | 3k          | 12%        |
| Ref          | 13k    | 2k          | 15.4%      |
| ASR          | 13k    | 2k          | 15.4%      |
| Average      | 21.25k | 2.5k        | 12.48%     |

by the Linguistic Data Consortium. Before any experimentation, the following normalization rules were applied during a preprocessing cleaning process over the GW AFP dataset:

- XML tags and hyphens elimination
- Lowercase conversion
- Doubled punctuation marks elimination
- Apostrophes isolation
- Substitution of (?, !, ;. :, .) into "< SEG >"

The amount of tokens after the cleaning process for the GW AFP dataset is 477M, where 9% correspond to any punctuation mark (Table 2). This proportion is very similar to the Nicola et al. (2013) WSJ’s dataset presented in Table 1, which consists of newspaper text. 80% of the tokens were used during training and validation while 20% was used exclusively for testing.

Table 2: GW AFP dataset statistics.

| Dataset | tokens | punctuation | percentage |
|---------|--------|-------------|------------|
| GW AFP  | 477M   | 43M         | 9%         |

3.2. Metrics

To evaluate our models we considered necessary two types of metrics. At a first glance we opted for Accuracy (2), a general metric that could measure the performance of the models regardless the class. Nevertheless, given the disparity of samples between the two classes, Accuracy is very likely to be biased: so Precision (3), Recall (4) and F1 (5) metrics were calculated for each one of the two classes.

\[
\text{Accuracy} = \frac{\#\text{correctly predicted samples}}{\#\text{samples}} \quad (2)
\]

\[
\text{Precision}_{ci} = \frac{\#\text{correctly predicted samples}_{ci}}{\#\text{total predicted samples}_{ci}} \quad (3)
\]

\[
\text{Recall}_{ci} = \frac{\#\text{correctly predicted samples}_{ci}}{\#\text{total samples}_{ci}} \quad (4)
\]

\[
F1_{ci} = 2 \times \frac{\text{Precision}_{ci} \times \text{Recall}_{ci}}{\text{Precision}_{ci} + \text{Recall}_{ci}} \quad (5)
\]

3.3. Results

Three different baselines are shown in Table 3. In their experiments, Authors of [3] compute only Precision, Recall and F1 for the “sentence boundary” class. CNN-2 and CNN-2A refer to the same convolutional neural network model but in CNN-2A it only takes into account half the value of softmax output for the “no sentence boundary” class. This variation equilibrates Precision and Recall of CNN-2 reaching a F1 score value of 0.788.

CNN-A refers to the untrained CNN-A model. We wanted to have this as a baseline to visualize how the unbalanced nature of the samples impacts all measures and may mislead general metrics like Accuracy.

Accuracy over all the proposed models is higher than in CCN-A, reaching the higher score for CNN-B. Concerning Precision, CNN-B and CNN-A overperform for different classes. CNN-2A reflects a higher Recall than the rest of the baselines and models. Finally, F1 score for both classes is higher in CNN-B.

Given the similar results of the models we wanted to see the behavior of the models during training process. Cross entropy during training process is plotted in Figures 2 to 4. The three curves show a similar behavior and converge in a value below 0.09. CNN-B slightly overperforms the rest of the models (Table 4).
Table 3: Results for CNN models.

| Model     | Accuracy | Precision | Recall | F1  |
|-----------|----------|-----------|--------|-----|
| NO SEG    | 0.836    | 0.723     | 0.585  | 0.775|
| SEG       | 0.723    | 0.799     | 0.585  | 0.788|
| NO SEG    | 0.909    | 0.718     | 0.585  | 0.778|
| SEG       | 0.952    | 0.801     | 0.585  | 0.787|
| CNN-2 [3] | -        | -         | 0.836  | -   |
| CNN-2A [3]| -        | -         | 0.776  | -   |
| CNN-A_u  | 0.909    | 0.799     | 0.585  | 0.788|
| CNN-A    | 0.965    | 0.981     | 0.585  | 0.795|
| CNN-B    | 0.963    | 0.975     | 0.845  | 0.980|
| CNN-C    | 0.963    | 0.974     | 0.832  | 0.980|

Figure 4: Cross entropy (CNN-C)

Table 4: Cross entropy during training

| Model | Cross entropy |
|-------|---------------|
| CNN-A | 0.082         |
| CNN-B | 0.080         |
| CNN-C | 0.089         |

4. Conclusions

In this paper we combined CNN networks with SLI vectors to tackle the problem of sentences boundary detection as a binary classification task for French. We used a big written dataset instead of standard size transcriptions to reuse the trained models in further transcriptions. SLI vectors, that represent words as the sum of their characters vectors taking advantage of their morphology, showed to be very effective working with our three CNN models. In a future, we will include other languages like Arabic and English. Also we will reuse the trained models in a variety of ASR transcriptions of newscasts and reports domain.

5. Acknowledgements

We would like to acknowledge the support of Chist-Era for funding this work through the Access Multilingual Information opinionS (AMIS), (France - Europe) project.

6. References

[1] D. Fohr, O. Mella, and I. Illina, “New paradigm in speech recognition: Deep neural networks,” in IEEE International Conference on Information Systems and Economic Intelligence, 2017.
[2] N.-T. Le, B. Lecouteux, and L. Besacier, “Disentangling ASR and MT Errors in Speech Translation,” in MT Summit 2017, Nagoya, Japan, Sep. 2017. [Online]. Available: https://hal.archives-ouvertes.fr/hal-01580877
[3] X. Che, C. Wang, H. Yang, and C. Meinel, “Punctuation prediction for unsegmented transcript based on word vector,” in The 10th International Conference on Language Resources and Evaluation (LREC), 2016.
[4] W. Lu and H. T. Ng, “Better punctuation prediction with dynamic conditional random fields,” in Proceedings of the 2010 conference on empirical methods in natural language processing. Association for Computational Linguistics, 2010, pp. 177–186.
[5] O. Tilk and T. Alumë, “Bidirectional recurrent neural network with attention mechanism for punctuation restoration,” Interspeech 2016, pp. 3047–3051, 2016.
[6] S. Peitz, M. Freitag, and H. Ney, “Better punctuation prediction with hierarchical phrase-based translation,” in Proc. of the Int. Workshop on Spoken Language Translation (IWSLT), South Lake Tahoe, CA, USA, 2014.
[7] J. Zribi, I. Kammoun, M. Ellouze, L. Belguith, and P. Blache, “Sentence boundary detection for transcribed tunisian arabic,” Bochumer Linguistische Arbeitsberichte, p. 323, 2016.
[8] J. Kolář and L. Lamel, “Development and evaluation of automatic punctuation for french and english speech-to-text,” in Thirteenth Annual Conference of the International Speech Communication Association, 2012.
[9] F. Batista, H. Moniz, I. Trancoso, and N. Mamede, “Bilingual experiments on automatic recovery of capitalization and punctuation of automatic speech transcripts,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 20, no. 2, pp. 474–485, 2012.
[10] U. Nicola, B. Maximilian, and V. Paul, “Improved models for automatic punctuation prediction for spoken and written text,” in Proceedings of INTERSPEECH, 2013.
[11] N. Ueffing, M. Bissani, and P. Voizil, “Improved models for automatic punctuation prediction for spoken and written text.” in INTERSPEECH, 2013, pp. 3097–3101.
[12] M. Igras and B. Ziolkó, “Detection of sentence boundaries in polish based on acoustic cues,” Archives of Acoustics, vol. 41, no. 2, pp. 233–243, 2016.
[13] X. Che, S. Luo, H. Yang, and C. Meinel, “Sentence boundary detection based on parallel lexical and acoustic models.” in Interspeech, 2016, pp. 2528–2532.
[14] P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov, “Enriching word vectors with subword information,” arXiv preprint arXiv:1607.04606, 2016.
[15] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” in Advances in neural information processing systems, 2013, pp. 3111–3119.
[16] J. Pennington, R. Socher, and C. D. Manning, “Glove: Global vectors for word representation,” in Empirical Methods in Natural Language Processing (EMNLP), 2014, pp. 1532–1543. [Online]. Available: http://www.aclweb.org/anthology/D14-1162.

[17] A. Mnih and K. Kavukcuoglu, “Learning word embeddings efficiently with noise-contrastive estimation,” in Advances in Neural Information Processing Systems 26, C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2013, pp. 2265–2273. [Online]. Available: http://papers.nips.cc/paper/5165-learning-word-embeddings-efficiently-with-noise-contrastive-estimation.pdf.

[18] O. Levy and Y. Goldberg, “Linguistic regularities in sparse and explicit word representations,” in Proceedings of the eighteenth conference on computational natural language learning, 2014, pp. 171–180.

[19] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in neural information processing systems, 2012, pp. 1097–1105.

[20] E. Maggiori, Y. Tarabalka, G. Charpiat, and P. Alliez, “Convolutional neural networks for large-scale remote-sensing image classification,” IEEE Transactions on Geoscience and Remote Sensing, vol. 55, no. 2, pp. 645–657, 2017.

[21] Y. Kim, “Convolutional neural networks for sentence classification,” arXiv preprint arXiv:1408.5882, 2014.

[22] R. Collobert and J. Weston, “A unified architecture for natural language processing: Deep neural networks with multitask learning,” in Proceedings of the 25th international conference on Machine learning. ACM, 2008, pp. 160–167.

[23] D. Palaz, G. Synnaeve, and R. Collobert, “Jointly learning to locate and classify words using convolutional networks,” in INTERSPEECH, 2016, pp. 2741–2745.