Joint Learning of Correlated Sequence Labelling Tasks Using Bidirectional Recurrent Neural Networks

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Abstract

The stream of words produced by Automatic Speech Recognition (ASR) systems is devoid of any punctuations and formatting. Most natural language processing applications usually expect segmented and well-formatted texts as input, which is not available in ASR output. This paper proposes a novel technique of jointly modelling multiple correlated tasks such as punctuation and capitalization using bidirectional recurrent neural networks, which leads to improved performance for each of these tasks. This method can be extended for joint modelling of any other correlated multiple sequence labelling tasks.

1. Introduction

Sequence labelling involves the assignment of a categorical label to each element of a sequence of observed values. Some common examples include punctuation prediction for automatic speech recognition (ASR) transcripts, capitalization recovery (i.e. restoring the case of the lowercased words, a.k.a. truecasing), part-of-speech tagging (POS), named entity recognition (NER), and more. In this work we address the task of multiple sequence labelling, where the goal is to assign multiple categorical labels to every element of the same sequence (for example, predict both the punctuation and capitalization for a given ASR speech transcript). We specifically address the scenario in which the multiple sequence labelling tasks are correlated. Consider the following two examples,

1. …and it hasn’t been refined enough yet. It needs to work on until it can speak fluently
2. This young doctor, Tom Ferguson, was the medical editor of the Whole Earth Catalog.

The first example shows the co-occurrence of capitalization preceded by a PERIOD. In the second example, the two COM- MAs surround capitalized proper nouns. Such co-occurrences illustrate the fact that punctuation and capitalization are two correlated tasks that should benefit from each other. We refer to these kinds of sequence labelling tasks as correlated multiple sequence labelling and propose a novel approach using a bidirectional recurrent neural network (BiRNN) which is trained jointly for prediction across such tasks.

Speeches are often transcribed by ASR systems that convert the audio signals into a stream of words. Apart from usually having a high word error rate, this stream is also devoid of the standard textual structure present in written texts. The structural aspects include punctuation, capitalization, and numeric data formatting, such as digits, dates, and phone numbers. Recovering the structure from raw word transcripts is essential for two main reasons. First, the structure enhances the readability and understanding of the transcripts. Second, its recovery enables the subsequent text processing and makes it more accurate. Many works have shown the impact of the structure recovery for tasks such as summarization, part-of-speech (POS) tagging, machine translation and information extraction, among others.

We attempt to recover two aspects of structure, punctuation and capitalization, by casting them as correlated multiple sequence labelling problems. Earlier work proposed the idea of training multiple sequence labelling tasks together, and showed a slight improvement for POS and NER when combined with task-specific feature engineering. However, they assumed the availability of sentence segmentation and capitalization as inputs. The solution we propose does not assume any feature engineering and is suitable for speech transcripts, which do not come with punctuation or capitalization.

Earlier papers showed the usefulness of pause duration and prosodic features for punctuation prediction as compared to using textual features alone. In this work, our goal is to boost the accuracy of punctuation prediction without taking extra inputs such as prosodic features; we accomplish this by training the capitalization task jointly along with the punctuation task. To the best of our knowledge, this is the first RNN (BiRNN) based framework for joint training of correlated sequence labelling tasks. Moreover, this framework is general enough to be applicable for jointly training other correlated sequence labelling tasks such as POS tagging and NER.

In a nutshell, our contributions are the following:

- An RNN (BiRNN) - based joint learning framework for multiple correlated sequence labelling tasks, with no feature engineering.
- Improvement in punctuation prediction on speech transcripts by jointly training it with capitalization, without using any prosodic features. A similar improvement is also observed in capitalization.
- State-of-the-art performance in benchmark punctuation prediction dataset.

2. Correlated Multiple Sequence Labelling

Punctuation and capitalization are considered highly important for the structure recovery of ASR transcripts. There are various effective approaches to insert punctuation and specifically sentence boundaries into raw speech transcripts. In this work, we consider both punctuation and capitalization together, treating it as a correlated multiple sequence labelling problem, which is defined below:
that is, RNN PER'), mixed-case (e.g., 'McGill'), sentence-case (only first lowing: all-lowercase (e.g., 'hello'), all-uppercase (e.g., 'UP-
periods, commas, and question marks (Q-MARK below). Thus,
in existing literature due to their high frequency of occurrence:
we consider punctuation and capitalization tasks together. Typ-

ture the context in both directions (since the words to the right

Sentiment analysis, Namely, LSTM and GRU, along with multiple layers

illustrates this idea. We also incorporated architectural variants
of RNN, namely, LSTM and GRU, along with multiple layers

With the addition of dropout.

Joint Training Loss Function: The network formulated
above is defined for multiple correlated tasks (say K tasks) and
is capable of producing K sequences of outputs of the form
y^k_1,...,y^k_n. While predicting the outputs for the different tasks,
all the trainable parameters required until the computation of h,
are shared across all tasks and are trained jointly based on the
loss function defined over the outputs of all K tasks. We com-
pute the loss \( L^k \) for every task using with the standard cross-
entropy loss function. Then, based on predefined weights \( q_k \)
(over tasks), a weighted average of task-specific losses is taken
to produce the final loss \( L \) to be optimized:

\[
L = \sum_{k=1}^{K} q_k L^k
\]

This accumulated loss helps the network predict well across
all tasks. If the tasks are correlated (as in our case), then each
task should help the other tasks through the joint learning of
shared parameters. These shared parameters help produce cor-
related representations h, which can be used to generate pre-
dictions for all tasks.

3. Experiments

To corroborate the hypothesis that our jointly trained model
helps improve performance over the individual tasks, we exper-
imented on two different datasets, as described below. All our
models are evaluated based on precision, recall and F1 score,
for each punctuation class, and overall for all classes, as well as
with Slot Error Rate (SER)\(^1\).

3.1. Datasets

Intelligence Squared: This dataset was obtained from the In-
telligence Squared (IQ2 henceforth) debating television show,
whose transcripts are publicly available.\(^2\) We used 45 debates,
each containing talks by four speakers, from which we created
a train-validation-test split in a ratio of 60:10:30.

\(^1\)SER is the ratio of the total number of slot errors (substitutions,
deletions, and insertions) in the predicted set of labels, to the total
number of slots in the gold set of labels.

\(^2\)Evaluation on references only as ASR not available.

For k-th task being considered, the output sequence denoted
by \( y^k_1,...,y^k_n \), can be derived from the sequence of state vec-
tors \( s_1,...,s_n \), where \( s_i = [s^{W_i}, s^{E_i}] \) through different non-linear
functions \( O^k = g^k (f_i) \) as defined below:

\[
\begin{align*}
\mathbf{h}_i &= f(s_i) = \phi(Ws_i + b) \\
\mathbf{m}_i &= g^k (\mathbf{h}_i) = W^k \mathbf{h}_i + b^k \\
y^k_i &= \text{softmax}(\mathbf{m}_i)
\end{align*}
\]

In the above formulation, the concatenated state vector \( s \),
is transformed linearly and passed through the function \( \phi \in \{ \text{sigmoid}, \text{tanh}, \text{relu}, \text{linear} \} \) to produce a hidden layer vec-

tor \( \mathbf{h} \). To produce outputs for the different correlated tasks
in question, the vector \( \mathbf{h} \) is then passed through different branches
of linear + softmax, one branch for each of the tasks. That
is, for the k-th task, the output \( y^k \), is produced from the k-th
branch, which leads to the prediction of label \( l^k \). The set of

trainable parameters are \( \{ W, b, \{ W^k, b^k \} \} \) in addition to the
parameters defining the forward and backward RNNs. Figure 1

Given a sequence of words \( W = (w_1, w_2, w_3,...,w_n) \)
from a vocabulary \( V \), the task is to predict K labels
\( \{l^1_1, l^1_2,...,l^1_n\} \) corresponding to word \( w_i \), one for each
of the K tasks. This will produce K correlated output se-
quences of the form \( O^k = \{l^k_1, l^k_2, ..., l^k_n\} \), one for each of
the K sequence labelling tasks. Here, labels for different
tasks come from different label space, as in K-SER.1

Following the above definition, \( K = 1 \) trivially implies a sin-
gle sequence labelling problem. In our setting, \( K = 2 \) when
we consider punctuation and capitalization tasks together. Typ-
ically, three punctuation marks have received the most attention
in existing literature due to their high frequency of occurrence:
periods, commas, and question marks (Q-MARK below). Thus,
\( L^1 = \{ \text{COMMA}, \text{PERIOD}, \text{Q-MARK}, \text{NO-PUNCT} \} \), where
there is a high class imbalance tilted towards the NO-PUNCT
class. Here, the label \( l^1_i \) corresponds to the punctuation occur-
ing before the word \( w_i \). In case of capitalization, the label \( l^2_i \)
depicts the surface form of word \( w_i \), which can be any of the fol-

lowing: all-lowercase (e.g., ‘hello’), all-uppercase (e.g., ‘UP-
PER’), mixed-case (e.g., ‘McGill’), sentence-case (only first
letter capitalized, e.g., ‘London’) and single-letter-word-case
(e.g., ‘T’).

Given a sequence of n input vectors \( x_1,...,x_n \) and an initial
state vector \( s_0 \), an RNN generates a sequence of n state vectors
\( s_1,...,s_n \) alongside a sequence of n output vectors \( y_1,...,y_n \);
that is, \( RN (s_0, x_1,...,x_n) = s_1,...,s_n,y_1,...,y_n \). The input
vectors \( x \) are the latent embeddings (word2vec(RNN)) for each
word \( w_i \) in the sequence and \( s_i \) represents the state of the RNN
after observing the inputs \( x_1,...,x_i \). The output vector \( y_i \) is a
function of the corresponding state vector \( s_i \) and is then used for
further prediction. An RNN is defined by the following update
equations:

\[
\begin{align*}
\mathbf{s}_i &= R(\mathbf{x}_i, \mathbf{s}_{i-1}) \\
\mathbf{y}_i &= O(\mathbf{s}_i)
\end{align*}
\]

Different instantiations of \( R \) and \( O \) will result in different network structures
(Simple RNN, LSTM, GRU, etc.).

A bidirectional RNN consists of two parallel RNNs: one
running forward and another running backward. These cap-
ture the context in both directions (since the words to the right
have significant influence on a word label in addition to the
words to its left). Essentially, the same sequence of input vec-
tors \( x_1,...,x_n \) is fed to both RNNs to produce the sequence of
state vectors \( s^F_1,...,s^F_n \) from the forward RNN and \( s^B_1,...,s^B_n \)
from the backward RNN. Here we extend the bidirectional RNN
to model multiple correlated sequence labelling tasks together.
3.2. Experimental Setup

Data Preprocessing: Each training sequence consists of a random number of tokens (40 to 70 in our experiments), with the constraint that it must begin with a new sentence. The unfinished sentence forms the beginning of next training sequence. This scheme of generating training sequences prevents the model from always learning to predict a period or a question mark at the end of every sentence. For the validation and test datasets, we used a single consolidated sequence comprising all the sentences, to simulate a real ASR stream. This is not done for the training dataset to avoid memory issues with extremely long sequences. To evaluate our model on ASR transcripts, we mapped the punctuations and casing from the reference transcripts, based on Levenshtein alignment, as discussed in [13]. Since the mapping process is sensitive to ASR word errors, we adopted the approach in [26], and restricted the evaluation to only those punctuations for which the left and right context words have been recognized correctly by ASR. Similarly, we restricted capitalization evaluation to the words matching in the reference. For punctuation, we used the standard four classes as mentioned in Section 2 whereas for capitalization, sentence-case and mixed-case are merged as the latter occurs very rarely and has similar influence as the former.

Network Training and Tuning: We trained our model architecture using standard backpropagation in TensorFlow [23]. In our experiments, we trained two kinds of models: joint model (or Corr-BiRNN), which is trained jointly on punctuation and capitalization tasks, and task-specific models (or Single-BiRNN), which were trained separately for each of the two tasks. We carried out extensive hyper-parameter tuning for both the joint model and the separate task-specific models, for the IQ2 and TED datasets. The tuned hyper-parameters included: the number of layers and the number of hidden units per layer in the BiRNN, RNN dropout rate, RNN output dropout rate, type of RNN (Simple RNN, LSTM or GRU), the number of units in the outer hidden layer, hidden layer activation function, task-specific loss weights, and batch size. The best hyper-parameter setting for the joint model as well as the task-specific models was selected based on SER performance on the validation set for the task at hand. We then evaluated the selected settings on the reference transcripts of the corresponding test datasets and on test ASR (available for TED only) for the respective tasks. Please note the best hyper-parameter setting for a punctuation task-specific model may not be the same as that of a capitalization task-specific model. In other words, Single-BiRNN may have different settings selected based on the task at hand. Similarly, for Corr-BiRNN, different settings give best validation SER performance on punctuation and capitalization tasks.

4. Results and Discussion

The test evaluations are reported in Tables 1-3. For all tables, each row contains test evaluation metrics for the hyper-parameter setting that was selected based on validation SER performance of the task being considered. Table 4 shows example outputs of our models on ASR compared to gold labels, created by mapping from reference.

For the IQ2 dataset (refer Table 1), the joint training results in improved performance on both of the tasks, as compared to models trained for each of the individual tasks. This is consistent based on overall F1-score as well as SER metrics.

For the TED capitalization task (Table 3), the Corr-BiRNN model outperforms Single-BiRNN model performance in terms of F1 score for all test datasets across both Reference and ASR transcripts (this includes test-set-1 and test-set-2, though results are shown only for test-set-2 in the interest of space). However, improvement is not seen in UPPERCASE performance; this is expected since this label was not correlated with any punctuation.

Regarding the TED punctuation task (Table 2), the Corr-BiRNN model outperforms Single-BiRNN model performance (F1 score) for punctuation task in case of test-set-1 (Ref.), test-set-1 (ASR) and test-set-2 (Ref.); that is, in three out of four cases. For test-set-2 (ASR), the Single-BiRNN model is only marginally better than the Corr-BiRNN model. This can be attributed to the fact that the Single-BiRNN model was chosen based on the validation performance on TED reference transcripts, which are quite different from the ASR transcripts on which it is evaluated.

While comparing to the existing benchmarks on the TED punctuation task (refer Table 2), our Corr-BiRNN model fares significantly better on all fronts (especially Q-MARK with 22.9% gain in F1 score) compared to the existing benchmark [26] for test-set-1 (Ref.). In fact, its performance on test-set-1 (ASR) is better than the benchmark for test-set-1 (Ref.). It also outperforms the T-BRNN [27] benchmark in terms of COMMA and PERIOD for test-set-2 (Ref.), which are the more frequent punctuations, in addition to overall, measured in F1 score. For test-set-2 (ASR) though, we do not see improvement, mainly because the validation dataset is based on reference transcripts.

Despite having a much simpler model, in many cases we were able to beat the benchmark performance by T-BRNN [27], a more complex attention-based BiRNN model. This substantiates our claim that joint learning helps learning better representations than task-specific training for a particular task. Our simpler model has the added value of learning and predicting much faster than T-BRNN. In addition, our predictions are generated in one shot over the whole consolidated test sequence and does not need to follow window based prediction as in T-BRNN.

5. Related Work

Simple approaches for single sequence labelling that have been tried out are the unigram language model [8] and n-gram language model [29]. These models see limited fixed context around a word which may not be sufficient for prediction and they also face data sparsity issues as n increases. There are also classical approaches like Hidden Markov Models (HMM), maximum-entropy models (Max-Ent) and conditional random fields (CRF), all of which try to model a hidden state sequence corresponding to the observed word sequence as in [19, 20, 26, 51, 53, 57, 42]. However, these models are more difficult to train and construction of hand-crafted features is non-

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1. https://wit3.fbk.eu/mt.php?release=2012-03
2. Both Reference and ASR available.
3. http://iwslt2011.org/doku.php?id=06_evaluation
I ended up hiking up Mount Kilimanjaro. The highest mountain in Africa.

| Task | Model | COMMA | PERIOD | Q-MARK | OVERALL |
|------|-------|-------|--------|--------|---------|
| Punctuation | Single-BiRNN | 43.7 | 54.9 | 48.7 | 73.9 | 19.3 | 30.6 | 52.5 | 25.7 | 32.6 | 48.0 | 39.0 | 43.0 | 77.6 |
| Corr-BiRNN | 57.9 | 34.3 | 43.1 | 62.0 | 53.3 | 57.3 | 45.8 | 25.7 | 32.9 | 59.7 | 42.0 | 49.3 | 68.9 |

| Capitalization | Single-BiRNN | 96.1 | 63.2 | 76.4 | 87.0 | 55.7 | 67.9 | 99.9 | 98.2 | 99.0 | 89.6 | 61.3 | 72.9 | 45.3 |
| Corr-BiRNN | 95.1 | 63.2 | 76.0 | 80.9 | 65.3 | 72.3 | 97.2 | 98.0 | 98.9 | 84.2 | 69.5 | 76.2 | 43.0 |

Table 1: IQ2 results

Table 2: TED punctuation results. The figures mentioned in parenthesis refer to test-set-1, while the rest refer to test-set-2.

| Task | Model | COMMA | PERIOD | Q-MARK | OVERALL |
|------|-------|-------|--------|--------|---------|
| Punctuation | Single-BiRNN | (45.0) | (49.0) | (46.0) | (54.0) | (72.0) | (62.0) | (53.0) | (13.0) | (41.0) | (41.8) | (54.8) | (51.9) |
| Corr-BiRNN | 64.4 | 45.2 | 53.1 | 72.3 | 71.5 | 71.9 | 67.5 | 58.7 | 62.9 | 68.9 | 58.1 | 63.1 | 51.3 |
| ASR | T-BRNN | 65.5 | 47.1 | 54.8 | 73.3 | 72.5 | 72.9 | 70.7 | 63.0 | 66.7 | 70.0 | 59.7 | 64.4 | 49.7 |

Table 3: TED capitalization results. The figures are corresponding to test-set-2

| Task | Model | UPPERCASE | SENTENCE- CASE | SINGLE-CASE | OVERALL |
|------|-------|-----------|---------------|-------------|---------|
| Punctuation | Single-BiRNN | 94.1 | 64.0 | 76.2 | 84.4 | 68.2 | 75.4 | 100.0 | 98.9 | 99.4 | 88.8 | 75.3 | 81.5 | 33.8 |
| Corr-BiRNN | 93.7 | 60.0 | 73.2 | 82.6 | 71.9 | 76.9 | 99.4 | 99.7 | 99.6 | 87.2 | 78.2 | 82.4 | 33.0 |
| ASR | Single-BiRNN | 87.5 | 87.5 | 87.5 | 80.4 | 58.6 | 67.8 | 100.0 | 99.1 | 99.5 | 86.7 | 69.2 | 76.9 | 41.3 |
| Corr-BiRNN | 87.5 | 87.5 | 87.5 | 76.3 | 62.2 | 68.6 | 99.4 | 100.0 | 99.7 | 83.3 | 72.1 | 77.3 | 42.3 |

Table 4: Examples of Joint vs. Task-specific model predictions on TED ASR dataset

| Task | Model | Gold | Capitalization |
|------|-------|------|----------------|
| Punctuation | Single-BiRNN | I ended up hiking up Mount Kilimanjaro, the highest mountain in Africa. | I wish you luck. May none of your non cancer cells become endangered species. |
| Corr-BiRNN | I ended up hiking up mount kilimanjaro, the highest mountain in africa. | I wish you may none of your non cancer cells become endangered species. |

Multiple sequence labelling tasks and their inter-dependence has been studied in great detail [12]. However, for tasks like POS tagging, NER and chunking, they assumed the availability of punctuation and capitalization, which is not true for ASR transcripts. More recently, joint prediction of punctuation and capitalization for transcribed speech has been attempted in [29], albeit using n-gram language models. In [32], a joint label space for punctuation and capitalization tasks is created, in order to predict labels for both tasks. This is, however, not scalable since label space can possibly explode with the introduction of more labels for each task. A few other works related to joint sequence labelling include joint parsing and punctuation prediction [33] using a CRF-based model, and disfluency detection alongside other NLP tasks like punctuation prediction [17] and dependency parsing [54], using classical solutions. In our work, we explore the joint learning of correlated multiple sequence labelling tasks like punctuation and capitalization using a deep-learning based approach without any feature engineering being involved.

6. Conclusion

Here we have shown the utility of models jointly trained on two ASR related tasks, punctuation and capitalization, to learn better representations for either of them. Our simple jointly-trained BiRNN model, trained only on lexical features, outperforms several complex models, which demonstrates its robustness and generalization ability. Future work will involve the joint training of a variety of other correlated NLP tasks.
7. References

[1] M. Schuster and K. Paliwal, "Bidirectional recurrent neural networks," *Trans. Sig. Proc.*, vol. 45, no. 11, pp. 2673–2681, Nov. 1997.

[2] Y. Liu, E. Shriberg, A. Stolcke, D. Hillard, M. Ostendorf, and M. Harper, "Enriching speech recognition with automatic detection of sentence boundaries and disfluencies," *Audio, Speech, and Language Processing, IEEE Transactions on*, vol. 14, no. 5, pp. 1526–1540, 2006.

[3] M. Shugrina, "Formattting time-aligned asr transcripts for readability," in *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, ser. HLT ’10. Association for Computational Linguistics, 2010, pp. 198–206.

[4] O. Tilk and T. Alumäe, “Lstm for punctuation restoration in speech transcripts,” in *Sixteenth Annual Conference of the International Speech Communication Association*, 2015.

[5] Y. Liu and S. Xie, “Impact of automatic sentence segmentation on meeting summarization,” in *Acoustics, Speech and Signal Processing*, 2008. ICASSP 2008. IEEE International Conference on. IEEE, 2008, pp. 5009–5012.

[6] J. Mrozinski, E. W. Whitaker, P. Chatain, and S. Furui, “Automatic sentence segmentation of speech for automatic summarization,” in *Acoustics, Speech and Signal Processing*, 2006. ICASSP 2006 Proceedings. 2006 IEEE International Conference on, vol. 1. IEEE, 2006, pp. 1–I.

[7] D. Hillard, Z. Huang, H. Ji, R. Grishman, D. Hakkani-Tür, M. Harper, M. Ostendorf, and W. Wang, “Impact of automatic comma prediction on pos/name tagging of speech,” in *2006 IEEE Spoken Language Technology Workshop*. IEEE, 2006, pp. 38–61.

[8] L. V. Lita, A. Itycheria, S. Roukos, and N. Kambhalla, “True-casing,” in *Proceedings of the 41st Annual Meeting on Association for Computational Linguistics-Volume 1*. Association for Computational Linguistics, 2003, pp. 152–159.

[9] M. Paulik, S. Rao, I. Lane, S. Vogel, and T. Schultz, “Sentence segmentation and punctuation recovery for spoken language translation,” in *Acoustics, Speech and Signal Processing*, 2008. ICASSP 2008. IEEE International Conference on. IEEE, 2008, pp. 5105–5108.

[10] E. Matusov, A. Mauser, and H. Ney, “Automatic sentence segmentation and punctuation prediction for spoken language translation,” in *ISWLT*, 2006, pp. 158–165.

[11] B. Favre, R. Grishman, D. Hillard, H. Ji, D. Hakkani-Tür, and M. Ostendorf, “Punctuating speech for information extraction,” in *Acoustics, Speech and Signal Processing*, 2008. ICASSP 2008. IEEE International Conference on. IEEE, 2008, pp. 5013–5016.

[12] R. Collobert, J. Weston, L. Bottou, M. Karlen, K. Kavukcuoglu, and P. Kuksa, “Natural language processing (almost) from scratch,” *Journal of Machine Learning Research*, vol. 12, no. Aug, pp. 2493–2537, 2011.

[13] J. Kolár and L. Lamel, “Development and evaluation of automatic punctuation for french and english speech-to-text.” in *INTERSPEECH*, 2012, pp. 1376–1379.

[14] I.-H. Kim and P. C. Woodland, “The use of prosody in a combined system for punctuation generation and speech recognition.” in *INTERSPEECH*, 2001, pp. 2757–2760.

[15] J. Huang and G. Zweig, “Maximum entropy model for punctuation annotation from speech.” in *INTERSPEECH*, 2002.

[16] T. Levy, V. Silber-Varod, and A. Moyal, “The effect of pitch, intensity and pause duration in punctuation detection,” in *Electrical & Electronics Engineers in Israel (IEEE)*, 2012 IEEE 27th Convention of. IEEE, 2012, pp. 1–4.

[17] D. Baron, E. Shriberg, and A. Stolcke, “Automatic punctuation and disfluency detection in multi-party meetings using prosodic and lexical cues.” *Channels*, vol. 20, no. 61, p. 41, 2002.

[18] V. Eidelman, Z. Huang, and M. Harper, “Lessons learned in part-of-speech tagging of conversational speech,” in *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*, ser. EMNLP ’10. Association for Computational Linguistics, 2010, pp. 821–831.

[19] X. Wang, H. T. Ng, and K. C. Sim, “Dynamic conditional random fields for joint sentence boundary and punctuation prediction.” in *INTERSPEECH*, 2012, pp. 1384–1387.

[20] C. Xu, L. Xie, G. Huang, X. Xiao, E. Chng, and H. Li, “A deep neural network approach for sentence boundary detection in broadcast news.” in *INTERSPEECH*, 2014, pp. 2887–2891.

[21] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their com- positionality,” in *Advances in Neural Information Processing Sys- tems 26*. Curran Associates, Inc., 2013, pp. 3111–3119.

[22] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997.

[23] K. Cho, B. van Merrienboer, Ç. Gülçehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, “Learning phrase representations using RNN encoder-decoder for statistical machine translation,” in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing*, EMNLP 2014, 2014, pp. 1724–1734.

[24] J. Makhoul, F. Kubala, R. Schwartz, R. Weischedel et al., “Performance measures for information extraction,” in *Proceedings of DARPA broadcast news workshop*, 1999, pp. 249–252.

[25] X. Che, C. Wang, H. Yang, and C. Meinel, “Punctuation predic- tion for unsegmented transcript based on word vector,” in *Pro- ceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016).* European Language Re- sources Association (ELRA), May 2016.

[26] N. Ueffing, M. Bisani, and P. Vozila, “Improved models for auto- matic punctuation prediction for spoken and written text.” in *IN- TERSPEECH*, F. Bimbot, C. Cerrisara, C. Fougeron, G. Graver, L. Lamel, F. Pellegrino, and P. Perrier, Eds. - ISCA, 2013, pp. 3097–3101.

[27] O. Tilk and T. Alumäe, “Bidirectional recurrent neural network with attention mechanism for punctuation restoration,” *Inter- speech 2016*, pp. 3047–3051, 2016.

[28] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard et al., “Tensorflow: A system for large-scale machine learning,” in *Proceedings of the 12th USENIX Symposium on Operating Systems Design and Im- plementation (OSDI)*, Savannah, Georgia, USA, 2016.

[29] A. Gravano, M. Jansche, and M. Bacchiani, “Restoring punctuation and capitalization in transcribed speech,” in *2009 IEEE Inter- national Conference on Acoustics, Speech and Signal Processing*. IEEE, 2009, pp. 4741–4744.

[30] X. Ma and E. Hovy, “End-to-end sequence labeling via bi- directional lstm-cnns-crf,” in *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, August 2016, pp. 1064–1074.

[31] 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.

[32] T. Baldwin and M. P. A. K. Joseph, “Restoring punctuation and casing in english text,” in *Australasian Joint Conference on Artificial Intelligence*. Springer, 2009, pp. 547–556.

[33] D. Zhang, S. Wu, N. Yang, and M. Li, “Punctuation prediction with transition-based parsing.” in *ACL (1)*, 2013, pp. 752–760.

[34] M. Honnibal and M. Johnson, “Joint incremental disfluency de- tection and dependency parsing,” *Transactions of the Association for Computational Linguistics*, vol. 2, pp. 131–142, 2014.