Span Classification with Structured Information for Disfluency Detection in Spoken Utterances

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Abstract

Existing approaches in disfluency detection focus on solving a token-level classification task for identifying and removing disfluencies in text. Moreover, most works focus on leveraging only contextual information captured by the linear sequences in text, thus ignoring the structured information in the text which is efficiently captured by dependency trees. In this paper, building on the span classification paradigm of entity recognition, we propose a novel architecture for detecting disfluencies in transcripts from spoken utterances, incorporating both contextual information through transformers and long-distance structured information captured by dependency trees, through graph convolutional networks (GCNs). Experimental results show that our proposed model achieves state-of-the-art results on the widely used English Switchboard dataset for disfluency detection and outperforms prior-art by a significant margin. We make all our codes publicly available on GitHub¹.

Index Terms: disfluency detection, computational paralinguistics

1. Introduction

Speech is the natural way to communicate and is still the most preferred medium for communication. Unlike written text, in spoken utterances, humans often fail to pre-mediate what they are going to say, leading to interruption of speech flow. This phenomenon, called disfluency, is a para-linguistic concept that is ubiquitous in human conversations. In the past decade, with Automatic Speech Recognition (ASR) systems achieving near-human performance in transcribing speech-to-text, the use of speech as an input to modern intelligent NLU systems has democratized to an enormous extent. However, these downstream systems, trained on fluent data, can easily get misled due to the presence of disfluencies. Thus disfluency detection and removal can output clean inputs for downstream NLP tasks, like dialogue systems, question answering, and machine translation. Moreover, disfluency detection also finds applications in automatic speech scoring [1, 2].

Figure 1 shows the general structure of a disfluency, whereby it can be divided into 3 main parts, reparandum, an optional interregnum, and repair. Disfluency detection with neural architectures generally focuses on identifying and removing reparandum. Furthermore, reparandum in disfluencies can primarily be categorized into 3 types, repetitions, restarts, and repairs, as shown in Table 1. Repetition occurs when linguistic materials repeat, usually in the form of partial words, words, or short phrases. Substitution occurs when linguistic materials are replaced to clarify a concept or idea. Deletion, also known as false restart, refers to abandoned linguistic materials.

Table 1: Different types of disfluencies.

| Type      | Example                                      |
|-----------|----------------------------------------------|
| Repair    | [I just + ] enjoy working                    |
| Repetition| it’s +{ uh } it’s almost like                |
| Restart   | we would like +] let’s go to the             |
| Deletion  | this +[ is ] just +] happened yesterday.     |
| Substitution| it’s nothing but wood +[ up here ][+]       |
|           | down here.                                   |

In the past decade, neural architectures have shown promising results in the task of disfluency detection, where most prior works in this domain primarily report results on SwitchBoard (SWBD) corpus and solve a sequence-tagging task. SWBD is a corpus of English telephonic conversations. The task of disfluency detection primarily focuses on detecting reparandums from segmented transcripts of individual SWBD utterances where every word in the utterance transcript is annotated as part of disfluency (or not). Most of these architectures, achieving state-of-the-art performance, solve a token-level classification task, which assigns a label to each token in the input sequence, specifying if the token is part of a disfluency or not. Though token classification is one of the most common choices for Entity Recognition (ER) and has several advantages, including not constraining the output to a single span and incorporating neighboring tag information when implemented with CRFs, we hypothesize that detecting disfluencies, especially reparandums, is different from ER where individual reparandum tokens seldom occur in isolation and make sense only when the entire span of tokens is considered together. Thus, building on the fact that models can make better semantic sense of reparandums out of spans of tokens, we propose to solve a span classification task for disfluency detection and devise models that can learn richer span representations and not token representations.

The primary task of span prediction is to tag a group of one or more contiguous tokens (up to a maximum specified length)
Disfluency detection systems can be divided into 4 primary categories. The first one makes use of noisy channel models [9, 10], which require a Tree Adjoining Grammar (TAG) based transducer in the channel model. The second category of models leverages phrase structure, which is often related to transition-based parsing and yet requires annotated syntactic structure [11, 12]. The third is the most common kind and frames the task as a sequence tagging task [13, 14], and the last one employs end-to-end Encoder-Decoder models [5, 15] to detect disfluent segments automatically. In this work, we focus on improving on the third kind, which is the sequence tagging approach. Earlier work on this learning paradigm mostly focused on devising new architecture using Bi-LSTMs, and CRFs [5]. Most recent work on this paradigm tried to alleviate the dependency on human-annotated datasets, where the authors [16, 17] propose self-supervised learning and data augmentation approaches to learning disfluencies and has proven to close the gap with supervised training. Very recently, [18] proposed to solve auxiliary sequence tagging tasks in addition to the original task of tagging disfluent tokens and serves as the current SOTA on the task of disfluency detection.

Though recent years have seen frequent paradigm shifts for the task of ER from token-level classification to span classification, this framework has been relatively under-studied. [3] conducts a detailed study on the complementary advantages and architectural biases provided by the latter. Additionally, leveraging parse trees to incorporate structured information for improving ER performance has seen growing interest among researchers [19, 20, 21].
3. Proposed Methodology

3.1. Problem Definition

The problem of disfluency detection can be formulated as a sequence tagging task where our primary aim is to identify tokens in spoken utterance transcripts which correspond to a reparandum. We denote the i-th sentence with T tokens as \( s_i = \{ w_i | t = 1, \cdots, T \} \), and our complete dataset denoted by \( \{ s_1, s_2, s_3, \cdots, s_N \} \), where \( N \) is the total number of sentences in our dataset. The corresponding label set is defined by \( \{ d_i, d_2, d_3, \cdots, d_N \} \) where \( d_i \) is the label sequence for each sentence and is denoted by \( d_i = \{ y_i | y = 1, \cdots, T \} \) where \( y_i \in Y \) and \( Y = \{ I, O \} \). \( I \) here stands for disfluent tokens and \( O \) stands for fluent tokens.

3.2. Proposed Architecture

Fig. 3 shows our proposed model architecture. As mentioned earlier, we integrate both structured and contextual information via token representations obtained from what we call Contextual and Structured Information layers, respectively. Post extraction and integration of these features, we pass them to a classification layer and follow a heuristic decoding strategy for tagging our sequences. Our Contextual Information Layer and decoding strategy are in line with the previous implementation in the span classification paradigm [22, 23, 24, 25, 26].

3.2.1. Contextual Information Layer

Given a sentence \( \{ w_1, w_2, w_3, \cdots, w_T \} \) with \( T \) words, the token representation layer outputs an encoding \( h_t \) for each token as follows:

\[
h_{1}, \cdots, h_{T} = \text{EMB}(w_{1}, \cdots, w_{T}) ,
\]

where \( \text{EMB}(\cdot) \) is a pre-trained contextualized text embedding model from the transformers family and \( h_t \in \mathbb{R}^{D} \).

3.2.2. Structured Information Layer

To incorporate the long-range dependencies and structured information between the tokens in the input sentence, we propose the use of an additional graph-encoded representation \( g_t \) for each token using dependency parse trees [27, 28]. We follow a simple approach whereby we use a Graph Convolution Network (GCN) to capture information along multiple dependency arcs between words in a sentence. Thus, given the context embeddings from the Bi-LSTM, the graph-encoded representation for each token \( t \) is obtained as follows:

\[
g_{1}, \cdots, g_{T} = \text{GCN}(h_{1}, \cdots, h_{T}) ,
\]

Post this step, we implement a gate for dynamically adjusting the contribution of features contributed by structured information in tokens, obtained from the GCN. Following the practice in previous work [29], we combine the representations from both Contextual and Structured information as follows:

\[
\text{gate} = \sigma \left( W_{g} h_t ; g_t + B_{g} \right)
\]

where \( W_{g} \in \mathbb{R}^{2d \times d} \) is a weight matrix and \( \sigma \) is the element-wise sigmoid function. The final graph-encoded representation for each token \( w_t \) is then obtained by \( g_t = \text{gate} \cdot g_t \).

Finally, for each token \( w_t \), the final representation fed to the span representation layer is \( z_t = [ h_t ; g_t ] \).

3.2.3. Span Representation Layer

After encoding the tokens in a sentence, we enumerate through all the possible \( m \) spans \( J = \{ j_1, \cdots, j_m \} \) up to a maximum specified length (in terms of the number of tokens) for sentence \( s = \{ w_1, \cdots, w_T \} \) and then re-assign a label \( y_i \in \{ I, O \} \) for each span \( j_i \). For example, for the sentence “NLP is um important”, all possible spans (or pairs of start and end indices) are \( \{ (1, 1), (2, 2), (3, 3), (4, 4), (1, 2), (2, 3), (2,4), (1, 3), (1,4) \} \), and all these spans are labelled \( O \) except (3, 3) which is labelled \( I \). We denote \( h_t \) and \( s_t \) as the start and end indices of span \( j_i \) respectively. We then formulate the vectorial representation of each span as the concatenation of the representations of the starting token \( z_{s_i} \in \mathbb{R}^{2d} \), the ending token \( z_{e_j} \in \mathbb{R}^{2d} \), and a length embedding \( \ell_i \in \mathbb{R}^{1 \times m} \). The length embedding is implemented as a look-up table and learnt while training the model. The final vector representation for each span fed into the span prediction layer is now \( \hat{y}_k = [ z_{s_k} ; z_{e_k} ; \ell_i ] \).

3.2.4. Span Prediction Layer

The final span representations \( \hat{y}_k \) is then passed through a linear transformation followed by a softmax operation as follows:

\[
P \left( \hat{y}_k \mid y_j \right) = \frac{\text{score} \left( \hat{y}_k, y_j \right)}{\sum_{y' \in Y} \text{score} \left( \hat{y}_k, y' \right)},
\]

\[
\text{score} \left( \hat{y}_k, y_j \right) = \exp \left( \hat{y}_k^\top y_j \right),
\]

where \( \hat{y}_k \) is the probability that the span \( j_i \) belongs to class \( k \) and \( y_k \) is a learnable representation of the class \( k \).

3.2.5. Decoding

Since our task of disfluency detection does not have overlapping spans, we follow the heuristic decoding method from literature for non-nested entities to avoid the prediction of overlapped spans. Specifically, for overlapped spans, we keep the span with the highest prediction probability and drop the others.

4. Experiments

4.1. Dataset

We evaluate our models on the human-annotated transcriptions [30] from the English Switchboard Dataset (SWBD) [31]. SWBD is one of the most widely used datasets for evaluating disfluency detection models and frameworks. Following [32], we split the entire dataset into training set sw23[\cdot], dps, development set sw4[5-9][\cdot], dps, and test set sw4[0-1][\cdot], dps. Next, for pre-processing the transcripts before feeding them into our model, we follow the pre-processing steps mentioned by [14] and convert all the text to lower-case and remove all punctuation and partial words.

4.2. Experimental Setup

All our models are implemented using the PyTorch [33] deep learning framework. We use Flair [34] to implement all our token-level classification baselines. For both our token-level classification and span classification models we use either of BERT\textsubscript{BASE} or ELECTRA\textsubscript{BASE} as our pre-trained contextualized token embedding model, and adopt the pre-trained checkpoints and implementation from the huggingface library [35]. We fine-tune our sequence tagging models with a batch size of 32 using adam optimizer with an initial learning rate of 5 ×
$10^{-5}$. The dimension of our length embedding $\text{len}$ in $\mathbb{R}^{\text{len}}$ is 300 and our Structured Information Layer has 2 layers of GCN.

4.3. Baselines and Compared Methods

For baselines, we resort to token-level classification baselines with or without Conditional Random Field (CRF) decoders [36] under the IO tagging scheme. CRF as a decoder has been a common choice for sequence labeling tasks due to its ability to incorporate neighboring label information by considering the state transition probability of neighboring labels in token-level classification models. Following prior-art, we choose BERT and ELECTRA from the transformers family as our contextualized text encoder for both the token-level classification and span classification setups.

4.4. Experimental Results

Table 2 shows the evaluation results on the SWBD test compared to prior-art on disfluency detection. Consistent with prior-art, we show the $F_1$ scores for all our approaches. As we clearly see, our best-proposed model (Span Classification w GCN) outperforms state-of-the-art (SOTA) [18] by 1.1% and our baselines by a significant margin. Though our span classification models alone report significant gains, integrating structured information with GCNs improves performance over it. Here, we want to reiterate the fact that including structured information for disfluency detection is a logical step and might steer further research in this direction. Additionally, in the next section, we also make an effort to analyze the benefits of adding structured information to our span classifier model.

Table 2: Evaluation results of our proposed model compared to the baselines and prior-art on the Switchboard test set. The best scores are denoted in bold.

| Model               | P  | R  | $F_1$ |
|---------------------|----|----|-------|
| Prior-art           |    |    |       |
| Semi-CRF [13]       | 90.0| 81.2| 85.4  |
| Bi-LSTM [4]         | 91.6| 80.3| 85.9  |
| Attention-based [5] | 91.6| 82.3| 86.7  |
| Transition-based [37]| 91.1| 84.1| 87.5  |
| Self-supervised [17]| 93.4| 87.3| 90.2  |
| Self-trained [11]   | 87.5| 93.8| 90.6  |
| EGBC [38]           | 95.7| 88.3| 91.8  |
| BERT fine-tune [38] | 94.7| 89.8| 92.2  |
| BERT-CRF-Aux [18]   | 94.6| 91.2| 92.9  |
| ELECTRA-CRF-Aux [18]| 94.8| 91.6| 93.1  |

| Our Experiments     |    |    |       |
|---------------------|----|----|-------|
| Our Baselines       |    |    |       |
| Token Classification BERT       | 91.8| 84.9| 88.2  |
| Token Classification ELECTRA     | 90.8| 88.3| 89.5  |
| Token Classification BERT-CRF    | 93.4| 82.6| 87.7  |
| Token Classification ELECTRA-CRF | 92.5| 87.2| 89.8  |
| Span Classification BERT         | 95.1| 93.0| 94.1  |
| Span Classification ELECTRA      | 90.1| 94.0| 92.3  |
| Span Classification BERT-GCN     | 95.2| 93.2| 94.2  |
| Span Classification ELECTRA-GCN  | 91.7| 94.0| 92.9  |

4.5. Qualitative Results Analysis

In this section, we first analyze with some example instances where span classification does better than token-level classification. Next, we also study the benefit of integrating graph-encoded structured information in our span classification model.

Span Classification vs. Token-level Classification—Highlighted words represent the prediction made by our span classifier and ground truth annotations, while the underlined words represent the predictions by our token-level classifier model.

1. i work part time at night and he works and my husband works full time days

2. so it was an age where it was thought it would be good for them to have the discipline that goes with having a pet

As we clearly see in both the examples, both spans are not obvious disfluencies other than the repetition in eg. 2 which was predicted right by the token-level classifier. We hypothesize that longer restarts and repairs like the ones in the examples are better captured by our span classifier, where the group of words with proper boundary supervision helps our span classifier better capture semantics than our token-level classifier which classifies tokens in isolation.

GCN vs w/o GCN—Highlighted words represent the prediction made by our span classifier with the GCN module and ground truth annotations, while the underlined words represent the predictions by our span classifier trained without it.

1. It’s in the winter typically it’s probably too cold to go out and do things like tennis

2. oh even where you do have the inspections you know the inspection is once a year

In the first example above, the word “typically” is a difficult fluent word to capture since it occurs between 2 disfluent words. However, the GCN guides our span classifier through the nominal subject dependency arc, which, when combined with contextual representation, helps our model understand that “typically” is semantically related to “cold”. Through the second example, we also hypothesize that our span classifier w/o GCN model might be biased to finding repeated nearby words and classify spans wrongly with any former span consisting of the repeated word. In this case, structured dependency of the former “inspections” with other nearby words helps the span classifier w GCN model classify it as fluent.

5. Conclusions

In this paper, we propose a novel model architecture for the task of disfluency detection in spoken utterance transcripts. Our proposed model achieves SOTA on the widely used English SWBD for disfluency detection. As part of future work, we would like to investigate how to better integrate structured and contextual information for better disfluency detection.
6. References

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