AUXILIARY SEQUENCE LABELING TASKS FOR DISFLUENCY DETECTION

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ABSTRACT
Detecting disfluencies in spontaneous speech is an important preprocessing step in natural language processing and speech recognition applications. In this paper, we propose a method utilizing named entity recognition (NER) and part-of-speech (POS) as auxiliary sequence labeling (SL) tasks for disfluency detection. First, we show that training a disfluency detection model with auxiliary SL tasks can improve its F-score in disfluency detection. Then, we analyze which auxiliary SL tasks are influential depending on baseline models. Experimental results on the widely used English Switchboard dataset show that our method outperforms the previous state-of-the-art in disfluency detection.

Index Terms— Disfluency Detection, Auxiliary Tasks, NER, POS

1. INTRODUCTION
Detecting disfluencies in spontaneous speech presents a significant challenge for natural language processing (NLP) problems such as parsing and machine translation [1, 2]. Speech disfluencies refer to any pauses in the normal flow of speech, including corrections, false starts, filled pauses, and repetitions. Figure 1 represents a standard annotation of disfluency structure. Three discrete parts of disfluency annotations: reparandum, interregnum, and repair are defined in [3]. The reparandum (RM) indicates words that the speaker intends to discard, interruption point (+) indicates the end of reparandum, interregnum (IM) indicates such as filled pauses, and discourse cue words and repair (RP) indicates correct words.

Fig. 1. An example of standard disfluency annotation in the English Switchboard dataset.

| Utterance |
|-----------|
| And I... would, once I start my forty(DATE), I’d like to do the forty-five(TIME) minutes(DATE) a(DATE) day(DATE) on the bike for a week, |

Table 1. Highlighted words represent ground-truth disfluencies, underlined words represent prediction of disfluency detection model, marked in red represent incorrect prediction, and the words in parentheses refer to named entities.

In general, interregnums are relatively easy to detect than reparandums because they have fixed phrases (e.g. "um", "uh"). As a result, the main challenge is detecting reparandums which having a free form of structure. As with most previous researches, we also focus on detecting reparandums. In disfluency detection, it is crucial not only to increase recall but also to reduce the case of predicting fluent speech is not fluent.

On the one hand, words representing a disfluency tend to be meaningless. On the other hand, words representing named entities are usually meaningful. For example, they can refer to locations, time, and names of people. Table 1 shows that utilizing named entities can be highly effective in the disfluency detection task. In Table 1 the incorrectly predicted words correspond to a named entity (DATE) while the ground-truth disfluencies are not named entities. Therefore, we assume that utilizing named entity recognition (NER) in the disfluency detection task can prevent mispredicting important words classified as named entities as disfluency, and eventually will improve the performance of disfluency detection.

Figure 2 represents the cases where RM and RP have the same POS tag type. Since the same POS tag sequence is used repeatedly, we hypothesize that if the POS tag is predicted at the same time during the disfluency prediction, it can lead to improved performance of disfluency detection. We also noticed that as a result of examining the pos tag distribution of words constituting the disfluencies, the ratio of ‘,’ (comma) and ‘prp (personal pronoun)’ tags accounts for 55%. These
two observations led us to use the POS prediction task for the disfluency detection task.

In this paper, we propose a method to increase the performance of disfluency detection by leveraging NER and POS tagging tasks, which are representative sequence labeling tasks. Although many approaches have been proposed for disfluency detection, most of the works only leverage disfluency label as target label [4, 5, 6, 7]. Our work is similar to [8] but differs in that they leverage self-supervised learning to solve the bottleneck of training data, and we leverage sequence labeling tasks as auxiliary tasks for disfluency detection. Our contributions can be summarized as follows:

- We propose the joint training method utilizing NER and POS as auxiliary tasks for disfluency detection.

- We show that on the widely used English Switchboard dataset, the proposed method can lead to achieving better F-score than not utilizing NER and POS tasks.

- The proposed method achieved state-of-the-art result over previous works on the English Switchboard dataset.

2. RELATED WORK

Disfluency Detection Task  Disfluency detection is commonly classified into parsing-based [9], translation-based [4] [10], and sequence-labeling-based [5] [11]. Many types of research have used sequence labeling models based on the begin-inside-outside (BIO) method that labels words as being inside or outside of a reparandum word sequence. Conditional random fields (CRFs) [12] [13], long short-term memory (LSTM) [11], and auto-correlational neural network (ACNN) [5] leverage the sequence labeling approach. [7] demonstrated that the combination of BiLSTM, self-attention, and adding noise during training helps to achieve a performance comparable to that of the BERT method [14]. [8] proposed two multi-task self-supervised learning methods to tackle the bottleneck of training data and achieved comparable performance by using less than 1% of the training data.

Sequence Labeling Tasks  Representative sequence labeling tasks include NER and POS tagging tasks. NER refers to the task of predicting entities and POS refers to predicting corresponding part of a speech tag, based on its context. Recent works for both tasks utilize convolutional or recurrent neural networks, transformer, and BERT with CRF layer [14, 15].

3. PROPOSED METHOD

3.1. Problem Definition

Let \( \Theta_s \) represent the shared features of disfluency detection, NER, and POS tasks. Also, let \( \Theta_d, \Theta_e, \) and \( \Theta_p \) represent task specific features for disfluency detection, NER, and POS. We can now define disfluency detection as a sequence-labeling problem. Given a sequence \( X = \{x_1, x_2, \cdots, x_n\} \) where \( n \) denotes the number of tokens, and its corresponding disfluency labels \( Y_d = \{y_1, y_2, \cdots, y_n\} \), the disfluency detection task aims to learn the function \( F^d(\Theta_s, \Theta_d) : X \rightarrow Y_d \).

Similarly, we define NER as a sequence-labeling problem, where given the same sequence \( X \) and its entity labels \( Y_e = \{y_1, y_2, \cdots, y_n\} \), learn the function \( F^e(\Theta_s, \Theta_e) : X \rightarrow Y_e \). Likewise, POS can be defined to learn the function \( F^p(\Theta_s, \Theta_p) : X \rightarrow Y_p \). Our objective is jointly training \( F^d(\Theta_s, \Theta_d), F^e(\Theta_s, \Theta_e), \) and \( F^p(\Theta_s, \Theta_p) \) to learn the better shared features \( \Theta_s \).

3.2. Contextual Representation

Recently, the transformer model, which has an encoder and decoder, was proposed [16]. Without recurrent layers, the transformer can encode contextual information using only self-attention mechanisms. Based on the transformer architecture, pre-trained language models such as BERT [14] and ELECTRA [17] have been proposed achieving state-of-the-art results on various NLP tasks.

In this work, we build our encoder based on transformer, BERT, and ELECTRA models. The sequence of token representation \( W = [w_1, \cdots, w_n] \) is fed into the encoder. Then the contextual representation \( H = [h_1, \cdots, h_n] \) is obtained representing the history of context.

3.3. Labeling with Conditional Random Field Decoder

While the contextual representation generated by the encoder can take into account the attention between inputs, considering the information of neighboring labels is also important. A CRF can consider the state transition probability between neighboring labels decoding the most probable output label sequence [18]. Therefore, we adopted a CRF on top of the encoder to label disfluencies, named entities, and part-of-speech tags efficiently. The objective of the CRF is to maximize the log probability of the ground label \( \log P(Y|H) \), where \( H \) denotes the contextual representation and \( Y \) denotes the sequence of ground labels.
3.4. Joint Training Objective

Using three CRF decoders, we define the negative log likelihood loss for disfluency detection as $L_d = - \sum \log p(y^d_t | h_t)$, NER as $L_e = - \sum \log p(y^e_t | h_t)$, and POS as $L_p = - \sum \log p(y^p_t | h_t)$, where $L_d$ denotes the CRF loss for disfluency detection, $L_e$ denotes the NER loss, and $L_p$ denotes the POS loss. To utilize NER and POS as auxiliary tasks, we define the joint training objective for disfluency detection as

$$L = L_d + \alpha (L_e + L_p),$$

where $\alpha$ is coefficients determining the degree of NER and POS loss. Each encoder has different performances according to the value of $\alpha$, and the results are described in the next section (see Figure 3). Note that we utilize NER and POS as auxiliary tasks in training time. Therefore, after training is completed, we use only one CRF layer for disfluency detection during inference time.

4. EXPERIMENTS

4.1. Dataset

**Switchboard** The English Switchboard dataset is the most widely used benchmark dataset for disfluency detection [19]. It is consists of conversational speeches and annotated as in Figure 1. Following [5], we defined disfluency detection as a binary classification problem, where reparandum are annotated as disfluency, while all other words are annotated as fluent speech. We use sw[23]*.dff files as training, sw[4-9]*.dff files as validation, and sw[0-1]*.dff files as test dataset following the experiment settings as in [20].

We use the Flair [21, 22] NER model trained on the CoNLL NER dataset to assign named entities in a training data. Flair NER model was trained to predict 4 entities (e.g., ‘Locations (LOC)’, ‘miscellaneous (MISC)’, ‘organizations (ORG)’, and ‘persons (PER)’). Also, the POS tag is labeled on the Switchboard dataset, and we used it to train the POS tag prediction task.

4.2. Evaluation Metrics

We use token-based precision (P), recall (R), and F-score (F1) as the evaluation metrics following previous works [4, 8]. Since the performance may vary due to different initialization values for each experiment, we report averaged scores across five experiments of each model.

4.3. Baselines

To demonstrate the effectiveness of the proposed method, we build three baseline systems depending on which model to use as an encoder. We use the CRF as the decoder as described in 3.3.

Transformer-CRF The Transformer is an attention-based model [14]. The Transformer encoder layer has consisted of a multi-head self-attention and a feed-forward sub-layer.

BERT-CRF The BERT is a language model based on Transformer, and trained on a large-scale corpus with masked language model and next sentence prediction objectives [14].

ELECTRA-CRF The ELECTRA is also a language model like BERT but trained with more effective pre-training method [17]. In ELECTRA, instead of replacing some potion of token with [MASK] which corrupt inputs, replace some tokens with sampled from a generator. Then, a discriminator is trained to predict whether a generator replaces each token or not.

5. RESULTS AND DISCUSSION

5.1. Performance on the English Switchboard Dataset

| Model               | P     | R     | F1    |
|---------------------|-------|-------|-------|
| Semi-CRF [24]       | 90.0  | 81.2  | 85.4  |
| Bi-LSTM [11]        | 91.6  | 80.3  | 85.9  |
| Attention-based [25]| 91.6  | 82.3  | 86.7  |
| Transition-based [4] | 91.1  | 84.1  | 87.5  |
| Self-supervised [8] | 93.4  | 87.3  | 90.2  |
| Self-trained [26]   | 87.5  | 93.8  | 90.6  |
| EGBC [7]            | 95.7  | 88.3  | 91.8  |
| BERT fine-tune [7]  | 94.7  | 89.8  | 92.2  |
| Auxiliary SL Tasks (Ours) |
| Transformer-CRF     | 93.3  | 84.8  | 89.2  |
| BERT-CRF            | 94.6  | 91.2  | 92.9  |
| ELECTRA-CRF         | 94.8  | 91.6  | 93.1  |

Table 2. Evaluation results compared to the existing models on the Switchboard test dataset.

Table 2 reports the results of our methods and previous works on the Switchboard test dataset. In our auxiliary sequence-labeling (SL) tasks, NER and POS tasks are jointly utilized with disfluency detection task. The $\alpha$ of each model is chosen by best-achieved F-score on the dev dataset. Figure 3 reports F-scores of each model depending on the value of $\alpha$ for each auxiliary SL task on the Switchboard dev dataset. As a result, we set the value of $\alpha$ to 0.1 for Transformer-CRF, 0.5 for BERT-CRF, and 0.1 for ELECTRA-CRF.

From Table 2 we can observe that our BERT-CRF model with auxiliary SL tasks outperforms previous state-of-the-art model. Also, ELECTRA-CRF shows higher performance than BERT-CRF by 0.2 F-scores. As a result, we achieve new state-of-the-art result over previous works. Note that we do not compare our work with [10], since [10] tagged RM and IM as disfluency, while other works only tagged RM as disfluency including ours.
Fig. 3. F-scores of each model depending on the value of $\alpha$ for each auxiliary SL task on the Switchboard dev dataset.

| Model          | P   | R   | F1     |
|---------------|-----|-----|--------|
| Transformer-CRF | 92.3| 83.0| 87.4   |
| + NER         | 91.6| 85.6| 88.5   |
| + POS         | 92.8| 85.4| 89.0   |
| + NER + POS   | 93.3| 84.8| 89.2   |
| BERT-CRF      | 94.5| 90.0| 92.2   |
| + NER         | 95.4| 89.4| 92.3   |
| + POS         | 94.6| 91.3| 92.9   |
| + NER + POS   | 94.6| 91.2| 92.9   |
| ELECTRA-CRF   | 95.3| 90.1| 92.7   |
| + NER         | 95.8| 90.0| 92.8   |
| + POS         | 94.1| 92.1| 93.1   |
| + NER + POS   | 94.8| 91.6| 93.1   |

Table 3. Ablation analysis on the Switchboard test dataset.

5.2. Ablation Analysis

We conduct ablation analysis to investigate which auxiliary SL tasks are influential. Table 3 reports ablation analysis on the Switchboard test dataset. In the case of Transformer-CRF, when using the NER task together compared to not using any SL tasks, the F-score is 1.1% higher, and when POS is used, 1.6% higher. Furthermore, when NER and POS task are used together, the F-score is 1.8% higher. BERT-CRF shows 0.1% higher score when using the NER task, 0.7% higher score when using the POS task, and 0.7% higher score when using NER and POS task are used together. Finally, ELECTRA-CRF shows 0.1% higher score when using the NER task, 0.4% higher score when using the POS task, and 0.4% higher score when using NER and POS task are used together. Based on these results, the use of POS task in all models shows higher performance improvement than NER, and in the case of Transformer-CRF, using both NER and POS shows the highest performance improvement. We believe that this is because pre-trained language models learn some of the named entities or POS tag information during the pre-training procedure.

6. CONCLUSION

In this paper, we proposed the joint training method utilizing NER and POS as auxiliary tasks in disfluency detection. Through extensive evaluations, we showed that on the widely used English Switchboard dataset, the joint training method could lead to achieving better f-score and achieved state-of-the-art result. In future work, we will investigate whether auxiliary tasks are helpful in disfluency detection in other languages as well.

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