Disfluency Correction using Unsupervised and Semi-supervised Learning

Anonymous EACL submission

Abstract

Spoken language is different from written language in its style and structure. Disfluencies that appear in transcriptions from speech recognition systems generally hamper the performance of downstream NLP tasks. Thus, a disfluency correction system that converts disfluent to fluent text is of great value. This paper introduces a disfluency correction model that translates disfluent to fluent text, by drawing inspiration from recent encoder-decoder unsupervised style-transfer models for text. We also show large benefits in performance when utilizing a small sample of 500 parallel disfluent-fluent sentences in a semi-supervised way. Our unsupervised approach achieves a BLEU score of 79.39 on the Switchboard corpus test set, with further improvement to a BLEU score of 85.28 with semi-supervision. Both are comparable to two competitive fully-supervised models.

1 Introduction

Disfluencies are disruptions to the regular flow of speech, typically occurring in conversational speech. They include filler pauses such as *uh* and *um*, word repetitions, irregular elongations, discourse markers, conjunctions and restarts. For example, the disfluent sentence "well we're actually uh we're getting ready" has its fluent form as, "we're getting ready". Here, the words highlighted in green, blue and red refer to discourse, filler and restart disfluencies, respectively.

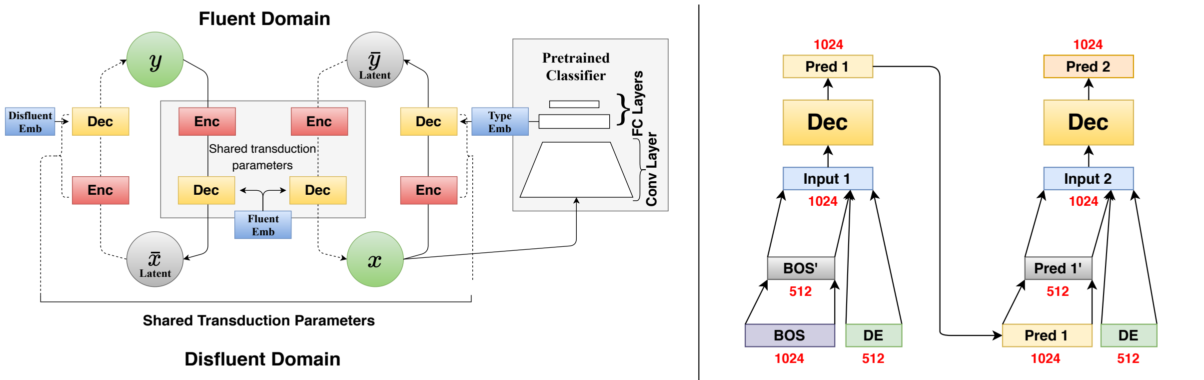
Disfluencies in text can alter its syntactic and semantic structure, thereby adversely effecting the performance of downstream NLP tasks such as information extraction, summarization, translation, and parsing (Charniak and Johnson, 2001; Johnson and Charniak, 2004). These tasks also employ pretrained language models that are typically trained to expect fluent text. This motivates the need for disfluency correction systems that convert disfluent to fluent text.

Prior work has predominantly focused on the problem of disfluency detection (Zayats et al., 2016; Wang et al., 2018; Dong et al., 2019). Inspired by recent work on unsupervised machine translation and style-transfer models for text, we propose an unsupervised encoder-decoder based model to tackle the problem of disfluency correction. Our model does not require access to a parallel corpus of disfluent and fluent sentences. We also show a semi-supervised variant of our model that uses a small amount of parallel disfluent-fluent text and significantly improves in performance. To our knowledge, this is the first work to use state-of-the-art unsupervised models for the task of disfluency correction. Our main contributions are as follows:

- We cast the problem of disfluency correction as one of translation from disfluent to fluent text and we propose an unsupervised transformer-based encoder-decoder model for disfluency correction.
- We compare and contrast an unsupervised and semi-supervised approach for disfluency correction, where the latter has access to a small amount of parallel text. We also implement fully-supervised approaches as a skyline and show how our models come very close in performance to these approaches which are very resource-intensive and require large amounts of parallel text.
- We show detailed ablation analyses across disfluency types and present a qualitative analysis of disfluency corrections that our model is able to achieve.

2 Related work

Current literature has primarily focused on disfluency detection in both speech and text in fully supervised settings (Wang et al., 2016; Georgila et al., 2010; Zayats et al., 2014; Tran et al., 2019;



(a) Style-transfer

(b) Induction of domain embedding

Figure 1: Illustration of (a) Style transfer model modified to use type embedding drawn from a pretrained CNN classifier. (b) Demonstration of domain embeddings into transformers' decoder. *Pred(i=1)* and *Input(i=1)* are decoder's prediction and input to the decoder at i_{th} time-step respectively.

Wang et al., 2018; Bach and Huang, 2019; Zayats et al., 2016; Lou and Johnson, 2020a). However, in most cases, simply removing disfluencies from an utterance can render the sentence ill-formed. More meaningful and syntactically well-formed utterances are generated by performing automatic disfluency removal from speech (Kaushik et al., 2010; Lou and Johnson, 2020b) and text (Wang et al., 2010; Honal and Schultz, 2005; Hassan et al., 2014). With the popularity of end-to-end spoken translation systems, several works translate fluent utterances from disfluent speech (Salesky et al., 2018; Ansari et al., 2020; Fukuda et al., 2020) or disfluent text (Cho et al., 2013; Saini et al., 2020). Most of these approaches work in a supervised setting or mitigate the lack of parallel disfluent-fluent text via data augmentation, model design, or incorporating domain knowledge of the language.

3 Our Approach

We draw inspiration from unsupervised neural machine translation models (Lample et al., 2017) and style transfer models (He et al., 2020) to design the disfluency correction model illustrated in Figure 1a. It consists of a single encoder and a single decoder, which are used to translate in both directions i.e. from disfluent to fluent text and vice-versa. To convey the direction of translation, the decoder is additionally conditioned using a *domain embedding* which signifies whether the input to the encoder is a fluent or disfluent sentence. More details about our framework are described below.

3.1 Unsupervised Disfluency Correction

Figure 1a clearly shows the two directions of translation. The model obtains latent disfluent and latent fluent utterances from the non-parallel fluent and disfluent sentences, respectively, which are further reconstructed back into fluent and disfluent sentences. We employ a backtranslation-based objective, followed by reconstruction for both domains i.e. disfluent and fluent text. For every mini-batch of training, soft translations for a domain are first generated (denoted by $\bar{\mathbf{x}}$ and $\bar{\mathbf{y}}$ in Figure 1a), and are subsequently translated back into their original domains to reconstruct the mini-batch of input sentences. The sum of token-level cross-entropy losses between the input and the reconstructed output serves as the reconstruction loss.

Borrowing from prior work on unsupervised style transfer model (He et al., 2020), the decoder is conditioned on a domain embedding that specifies the direction of translation. In this work, we employ two types of embeddings: A vanilla *binary domain embedding* that takes a bit as input to indicate whether the input text is fluent or disfluent and a *classifier-based domain embedding*. The latter is obtained from a trained standalone CNN-based classifier (Kim, 2014) that predicts the disfluency type of a disfluent input sentence. (Here, we assume that disfluency type labels are available for the disfluent sentences in our training data.) The penultimate layer from the classifier acts as our classifier embedding, which is further used to condition the decoder. We hypothesize that additional information about disfluency types via the classifier-based embedding might help guide the process of disfluency correction better.

Furthermore, similar to the noise models adopted by (He et al., 2020; Lample et al., 2017), a randomly sampled noisy version of every sentence in

Model	BLEU		METEOR	
	Dev	Test	Dev	Test
US (BiLSTM)	61.26	62.64	48.31	49.13
US (Transformer)	78.72	79.39	56.59	57.25
SS (Transformer)	83.85	85.28	57.77	58.35
Seq2Seq	87.23	88.08	56.65	59.36
BART	89.27	90.08	62.17	63.01

Table 1: BLEU and METEOR scores on the Switchboard dev and test sets. US and SS represent our unsupervised and semi-supervised approaches, respectively.

the input mini-batch is fed to the model, forcing it to behave like a denoising auto-encoder. We use noise perturbations (Lample et al., 2017) in the form of word-shuffle(α), word-blank(β) and word-dropout(γ) operations.

We explore two choices to implement our encoder-decoder modules: 1) BiLSTM-based (Bahdanau et al., 2015) and 2) Transformer-based (Vaswani et al., 2017). For the BiLSTM model, as proposed by (He et al., 2020), the BOS vector i.e. the input to the decoder at the first time-step is replaced by the domain embeddings. In the Transformer model, this conditioning needs to be carefully done. Figure 1b illustrates how we conditioned the transformer-based decoder. Dimensionality reduced word embedding is concatenated with the domain embedding *DE* at every time-step(t) to form the input for the decoder.

3.2 Semi-Supervised Disfluency Correction

Our unsupervised disfluency correction model can be easily fine-tuned using small amounts of parallel text, when available, lending itself to semi-supervised learning. The encoder-decoder modules are initialized using the unsupervised training described in the previous section, and further fine-tuned with a supervised cross-entropy loss using small amounts of parallel disfluent-fluent text. We do not make use of domain embeddings during semi-supervised training; inference is done as in the case of the unsupervised model i.e. with domain embeddings.

4 Experiments and Results

In this work, we use the Switchboard corpus (Godfrey et al., 1992) that includes telephonic conversations and their disfluency annotations (Schriberg, 1994; Zayats et al., 2014). We create a 70:15:15 train, test and validation split. Train set contains 110,964 sentences, whereas validation and test sets contain 11,889 disfluent-fluent sentence pairs.

4.1 Implementation Details

Our BiLSTM model uses a single layer of recurrent units of hidden size 750 with max pooling over a window size of 5. The noise perturbation parameters, α, β, γ were tuned on the validation set and set to 0. The model was trained for 15 epochs with 10 for annealing, using mini-batches of size 32, with Adam optimizer (Kingma and Ba, 2015) and a learning rate 0.01 linearly scheduled with rate of decrements of 0.5. Empirically, we also found it was important to allow gradients to pass through the backtranslations in order to generate meaningful sentences.

The transformer model uses 8 attention heads, word embedding and domain embedding dimensionalities of 1024 and 512. The noise perturbation parameters, α, β, γ are set as 3, 0.2, 0.1. Adam optimizer is used with an initial learning rate of 0.00001, with a linear scheduler and 10 warm-up steps. We used mini-batches of size 32. Dropout (Gal and Ghahramani, 2016) and label-smoothing (Szegedy et al., 2016) values were 0.3 and 0.1, respectively.

4.2 Results

Table 1 shows BLEU and METEOR scores between the gold fluent and the disfluency corrected output from five different models. We train two fully supervised skylines, based on Seq2Seq (Sutskever et al., 2014) and BART (Lewis et al., 2019), to compare against our approaches. The two supervised skylines use 55K pairs of parallel disfluent-fluent sentences during training and yields up to 90 BLEU score. In comparison, the unsupervised approach yields up to 80 BLEU score without any parallel data. Finetuning the unsupervised model with a small parallel corpus containing only 554 pairs (i.e. two orders of magnitude smaller than the complete set of 55K pairs) significantly bridges this gap and yields up to 85 BLEU score. In terms of METEOR scores, the difference between unsupervised and supervised approaches is much smaller, indicating that with respect to adequacy or content preservation, these approaches perform at par. These results also show that the last few additional BLEU points (i.e. the difference between BART and SS) come at a significant cost with having to create a large parallel corpus.

Using binary embeddings, we obtain 77.34 and 77.97 BLEU on the dev and test sets respectively,

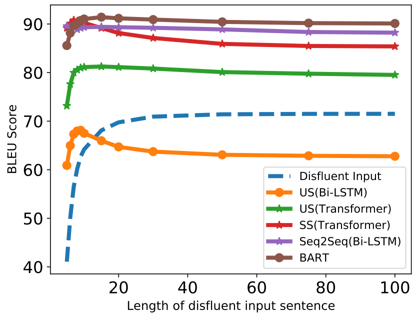


Figure 2: BLEU scores vs. input lengths.

whereas the disfluency-type classifier embedding yields 78.72 and 76.90 on the dev and test sets. The classifier embeddings do marginally improve performance. However, the BLEU scores obtained using the binary embeddings are almost comparable, which shows that even non-parallel text without any disfluency type labels can be effectively used by our proposed model.

Sentence Length: Figure 2 shows BLEU scores as a function of maximum sentence length on the test set. For the utterances smaller than 10 tokens, the BLEU score is highest; on longer sentences, the BLEU scores drop. This trend is uniform across all models. Our transformer-based model significantly outperforms the BiLSTM-based model on utterances of all lengths. Interestingly, our semi-supervised approach is very similar in performance to the fully supervised approach for smaller (<10 token) utterances.

Semi-supervised Learning: Table 2 shows the performance when our unsupervised model is fine-tuned with varying amounts of parallel text. By having access to only 554 parallel pairs (i.e. 1% total pairs), the performance improves by an impressive 5.89 BLEU on the test set. While BLEU improvements are a monotonically increasing function of the amount of parallel text, we see a trend of diminishing returns soon after the 1% mark.

%	Dev	Test
1	83.85	85.28
5	84.67	86.03
10	84.98	86.12
25	85.88	87.04
50	86.10	87.90
100	87.16	88.22

Table 2: % of samples vs BLEU.

Performance Across Disfluency Types: Intuitively, certain types of disfluencies (e.g. fillers) are easier to correct than others (e.g. edits). Table 3 reports the BLEU scores from all our models across disfluency types. Conjunctions and discourse disfluencies mark the easy end of the correction spectrum, while edits and asides mark the difficult end. (Edits are also hard to correct because of the lack of training data.)

Models	Set	all	conj	filler	restart	disc	edit	aside
US BiLSTM	Dev	61.26	62.68	56.96	53.76	53.84	49.06	37.07
	Test	62.64	63.60	58.45	54.92	55.39	52.51	37.25
US Transformer	Dev	78.72	80.17	76.86	72.39	71.91	63.20	48.56
	Test	79.39	80.18	77.47	73.06	73.19	64.35	45.71
SS Transformer	Dev	84.10	84.65	81.01	78.13	81.05	78.28	41.25
	Test	85.28	86.24	82.16	79.52	82.30	80.60	51.65
Seq2Seq	Dev	87.23	87.63	85.01	82.24	84.64	82.86	53.98
	Test	88.08	89.13	85.92	82.84	85.93	85.82	56.37
BART	Dev	89.27	88.98	87.41	84.99	87.52	85.45	53.88
	Test	90.08	89.79	88.59	85.60	88.57	87.13	55.68

Table 3: Disfluency type specific BLEU scores (conj: conjunctions and disc: discourse disfluencies).

	Disfluent	**BART**	**US(Bi-LSTM)**	**US(Xformer)**
disc., filler	so uh been a different turn	been a different turn	been a different turn	been a different turn
conj., rep.	but i i i find this whole	i find this whole	anyway i find it all	i find this whole
restart	it's you're you're taking words and developing a picture in your mind	you're taking words and developing a picture in your mind	it's you're taking chicken and tobacco words in a mind	it's taking words and developing and a picture in your mind
aside	i forgot sally's last name anyway it's a couple	i forgot sally's last name anyway it's a couple	gosh i forgot last name it's a couple of years	i forgot wordstart last name anyway it's a couple

Table 4: Analysis of generated text across all models.

Qualitative Analysis: Table 4 shows examples using three different models. All three models are able to remove simpler disfluencies (e.g. fillers and discourse) in shorter sentences. Conjunctions and repetitions are removed by all models except the BiLSTM model. The third example shows how the transformer model is much better than the BiLSTM model in terms of content retention and adequacy. The fourth example illustrates a case that is difficult for all models.

5 Conclusion

We propose an unsupervised disfluency correction model drawing motivation from prior work on unsupervised machine translation and style transfer. We investigate two kinds of domain embeddings for our model. We also present a semi-supervised disfluency correction approach, where we finetune our model using only about 500 parallel sentences, that comes very close in performance (based on BLEU scores) to a state-of-the-art fully supervised system.

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