Multi-Task Self-Supervised Learning for Disfluency Detection

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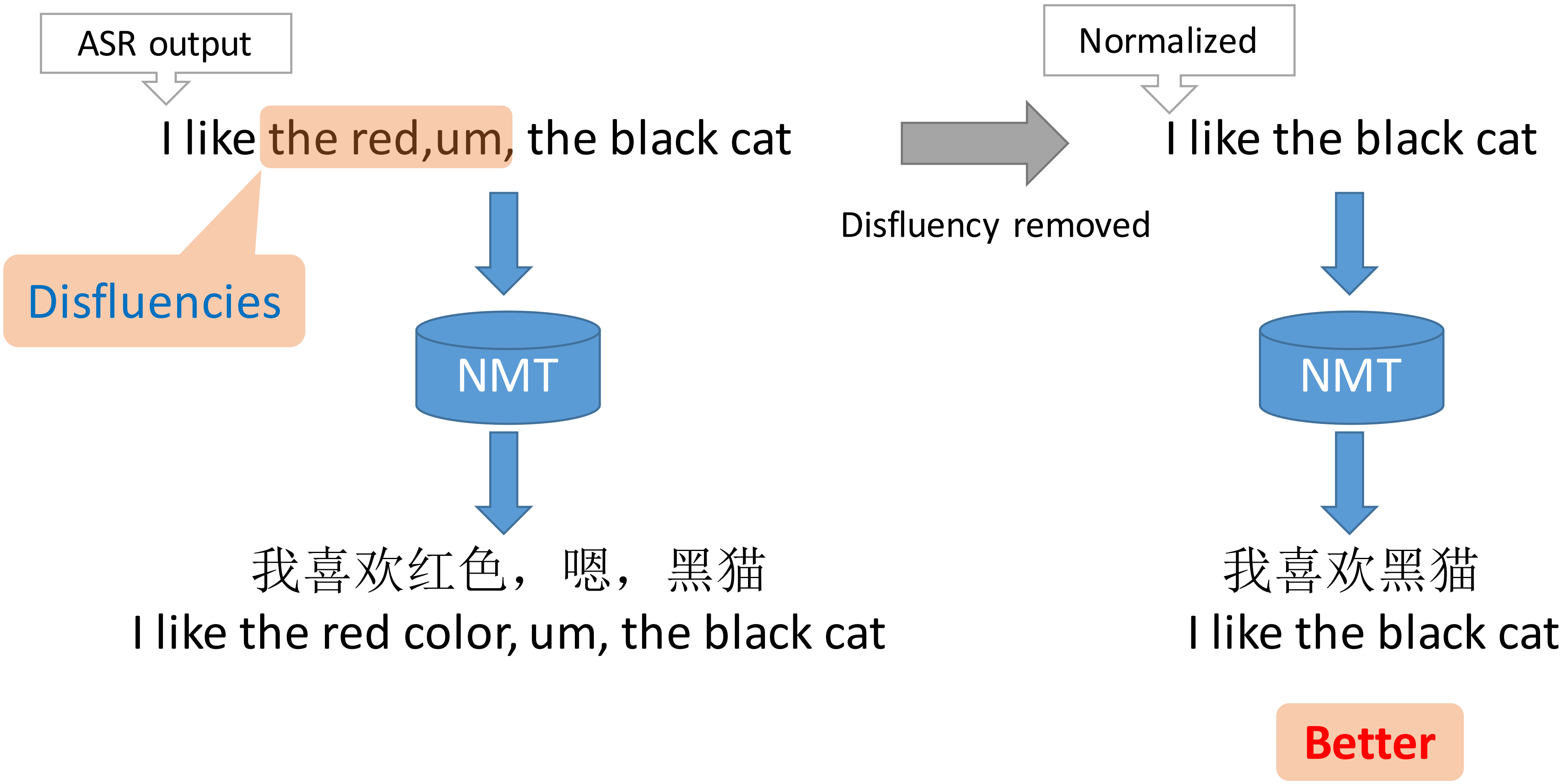
Disfluency Detection

- The transcribed speech text is mostly disfluent

$$\text{I want a flight [} \underbrace{\textit{to Boston}}_{\text{RM}} + \underbrace{\{\textit{um}\}}_{\text{IM}} \underbrace{\text{to Denver}}_{\text{RP}} \text{]}$$

Figure 1: A sentence from the English Switchboard corpus with disfluencies annotated. RM=Reparandum, IM=Interregnum, RP=Repair. The preceding RM is corrected by the following RP.

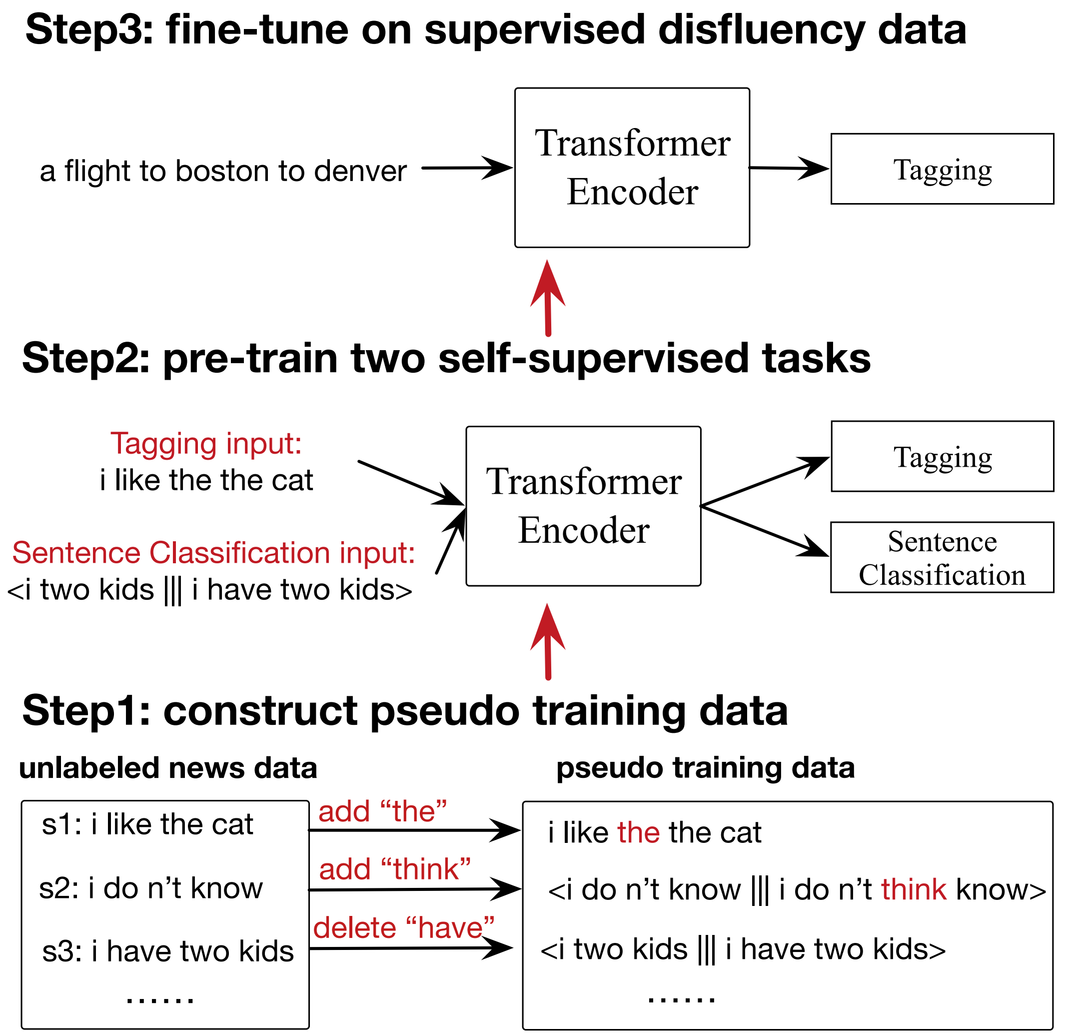
Disfluency Effect on Machine Translation



Our Motivations

- tackle the training data bottleneck
  - construct large-scale pseudo training data by randomly adding or deleting words from unlabeled news data
  - propose two self-supervised pre-training task

Our Model


Step3: fine-tune on supervised disfluency data
a flight to boston to denver
Transformer Encoder
Tagging
Step2: pre-train two self-supervised tasks
Tagging input:
i like the the cat
Sentence Classification input:
<i two kids ||| i have two kids>
Transformer Encoder
Tagging
Sentence Classification
Step1: construct pseudo training data
unlabeled news data
s1: i like the cat
s2: i do n't know
s3: i have two kids
......
add "the"
add "think"
delete "have"
pseudo training data
i like the the cat
<i do n't know ||| i do n't think know>
<i two kids ||| i have two kids>
......

Our Model

- Construct pseudo training data
  - Type1: S_{disf}
    - *Repetition*(*k*):the *m* (randomly selected from *one* to *six*) words starting from the position *k* are repeated.
    - *Inserting*(*k*) : randomly pick a *m*-gram (*m* is randomly selected from *one* to *six*) from the news corpus and insert it to the position *k*.
    - Eg: I like the cat → I think like the the cat
  - Type2: S_{del}
    - *Delete*(*k*) : for selected position *k*, *m* (randomly selected from *one* to *six*) words starting from this position are deleted.
    - Eg: he has two kids → he two kids

Our Model

- Tagging Task
  - detect the added noisy words in S_{disf}

eg: input: I think like the the cat

output: O D O D O O

- Classification Task
  - distinguish original sentences from grammatically-incorrect sentences.

eg: inout: <he has two kids ||| he two kids>

output: del_1

Our Model

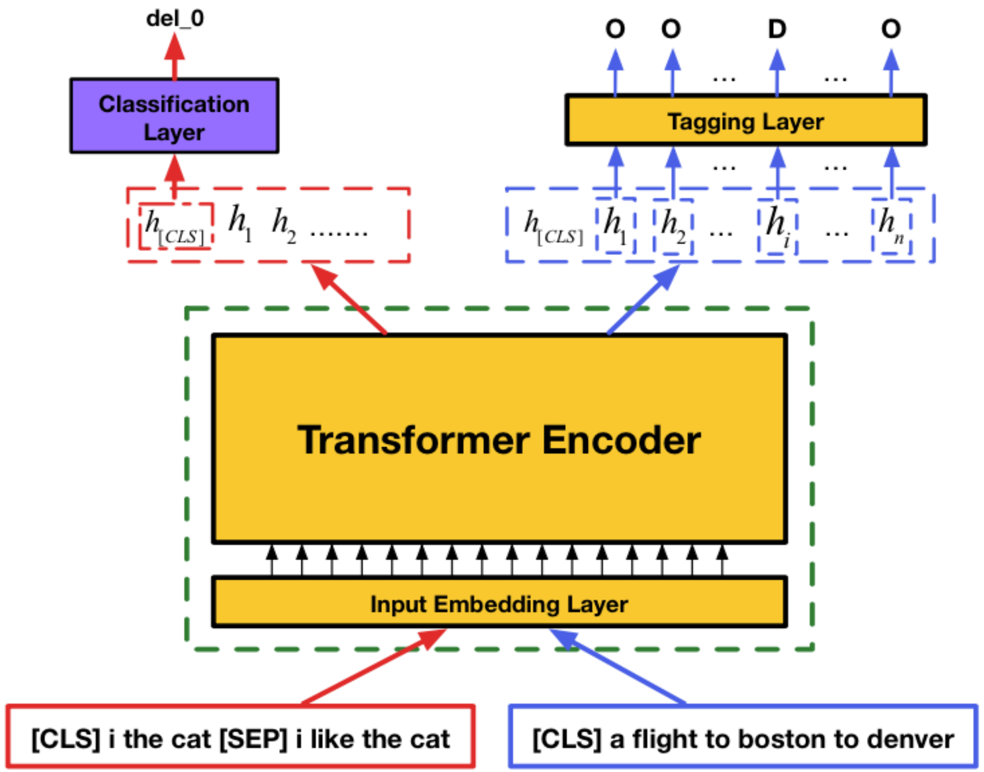


Figure 3: Model structure. The parameters of input embedding layer I, encoder layer E, and tagging layer T (yellow box) are shared among pre-training and fine-tuning

Experimental Setting

- Dataset
  - Pre-training data: 12 million
    - 3 million for tagging task
    - 9 million for classification task
  - English Switchboard corpus
    - About 100000 sentences for training data
- Model Size
  - 512 hidden units, 8 heads, 6 hidden layers

Experiment results

- Experiment results on the development and test data of English Switchboard data

Method	Full						1000 sents					
	Dev			Test			Dev			Test		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Transition-based	92.2	84.7	88.3	92.1	84.1	87.9	82.2	57.4	67.6	81.2	56.7	66.8
Transformer-based	86.5	70.4	77.6	86.1	71.5	78.1	78.2	51.3	62.0	79.1	51.1	62.1
Our self-supervised	92.9	88.1	**90.4**	93.4	87.3	**90.2**	90.0	82.8	**86.3**	88.6	83.7	**86.1**

Experiment results

- Comparison with the previous state-of-the-art methods

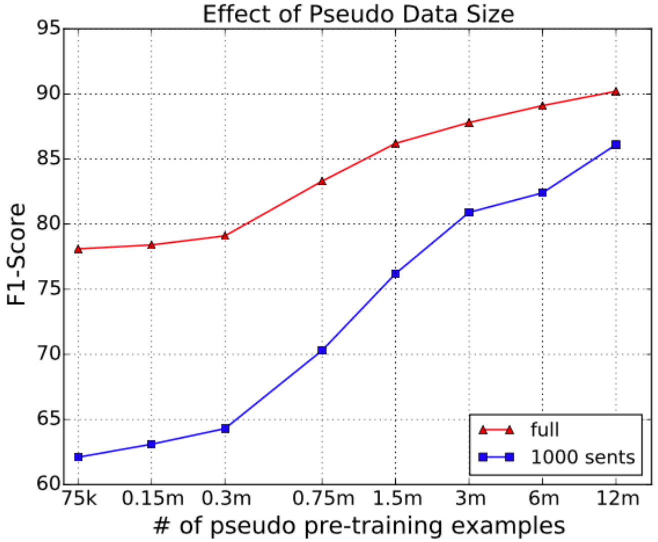
Method	P	R	F1
UBT (Wu et al. 2015)	90.3	80.5	85.1
Semi-CRF (Ferguson et al., 2015)	90.0	81.2	85.4
Bi-LSTM (Zayats et al., 2016)	91.8	80.6	85.9
LSTM-NCM (Lou and Johnson 2017)	-	-	86.8
Transition-based (Wang et al. 2017)	91.1	84.1	87.5
Our self-supervised (1000 sents)	88.6	83.7	86.1
Our self-supervised (Full)	**93.4**	**87.3**	**90.2**

Experiment results

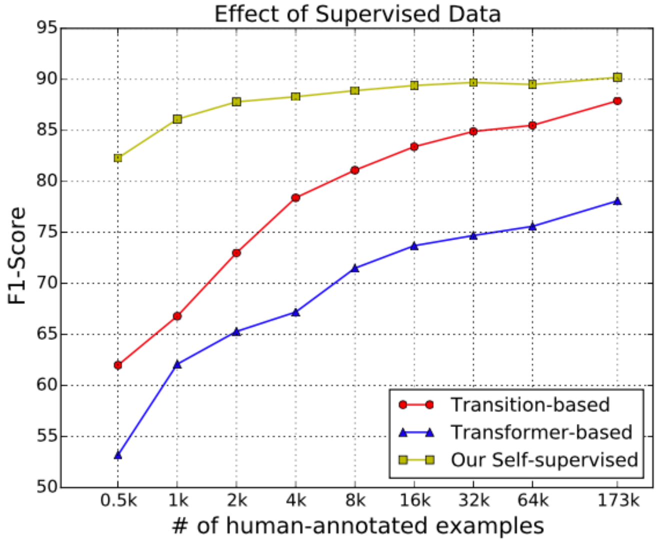
- Ablation over the two self-supervised tasks

Method	Full			1000 sents		
	P	R	F1	P	R	F1
Random-Initial	86.1	71.5	78.1	79.1	51.1	62.1
Tagging	91.8	84.0	87.7	85.1	79.6	82.3
Classification	91.2	83.1	87.0	83.2	78.3	80.7
Multi-Task	**93.4**	**87.3**	**90.2**	**88.6**	**83.7**	**86.1**

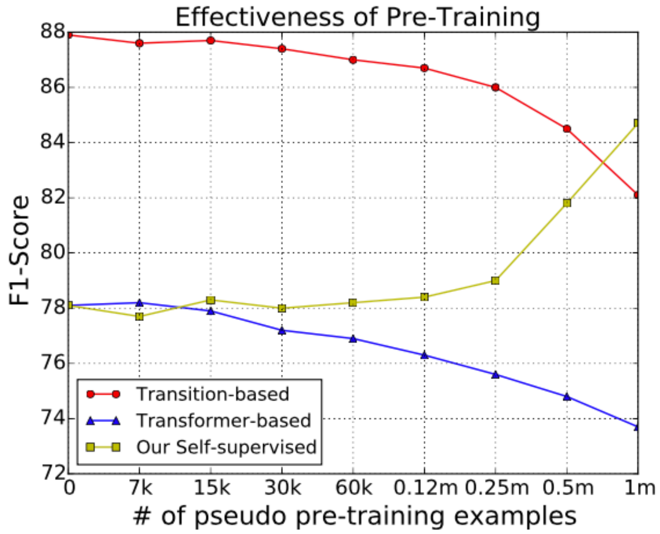
Experiment results



(a)



(b)



(c)

Experiment results

Comparison with BERT

Method	F1 (Full)	F1 (1000 sents)
Random-Initial	78.1	62.1
BERT-fine-tune	90.1	82.4
Our self-supervised	90.2	86.1
Combine	**91.4**	**87.8**

Table 7: Comparison with BERT. "random-initial" means training transformer network on gold disfluency detection data with random initialization. "combine" means concatenating hidden representations of BERT and our self-supervised models for fine-tuning.

Conclusion

- Propose two self-supervised tasks for disfluency detection to tackle the training data bottleneck.

- Experimental results show that our approach can achieve competitive performance compared to the previous systems by using less than 1% (1000 sentences) of the training data

Thank you!