



at SemEval-2019 Task 9: Semi-supervised Domain Adaptation using Tri-training for Suggestion Mining

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Suggestion Mining

- Mining sentences that contain suggestions in online discussions and reviews.
- Example Suggestion: “An electric kettle would have been a good addition to the room.”
- **Subtask A:** Domain specific sentence classification with training data from Microsoft Windows developer platform.
- **Subtask B:** Cross-domain classification on hotel reviews dataset.

Objective

- Evaluate recent advancements from **semi-supervised** and **transfer learning** literature to come up with a system for suggestion mining.
- **Subtask A**
 - Relatively small dataset
 - Class Imbalance
- **Transfer Learning:** Use pre-trained language models and transfer it to downstream tasks.
- **Subtask B**
 - No hand labelled training data.
- **Domain transfer using Semi-Supervised Learning:** Bootstrapping a model to come up with labels for data in a new domain and use it for training.

Code - <https://github.com/sai-prasanna/suggestion-mining-semeval19>

Built with Pytorch & AllenNLP

Tri-Training

Following the work of Ruder and Plank (2018) to apply classic tri-training, a semi-supervised learning technique for domain adaptation.

Algorithm 1 Tri-training

```

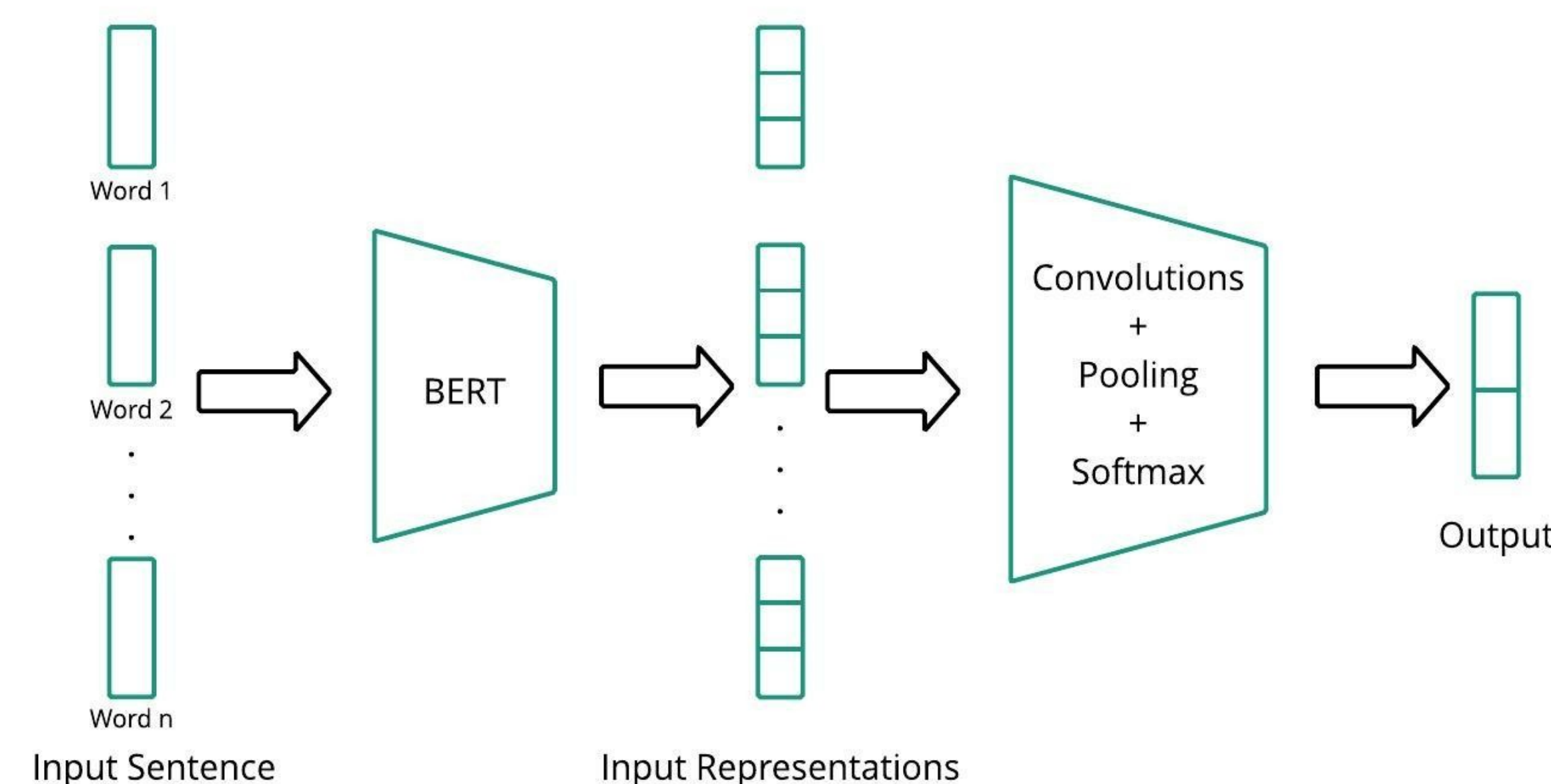
1:  $L \leftarrow$  Labelled Data ,  $|L| = m$ 
2:  $U \leftarrow$  Unlabelled Data ,  $|U| = n$ 
3: for  $i \leftarrow 1, 2, 3$  do
4:    $l_i \leftarrow$  BootstrapSamples( $L$ )
5: end for
6: repeat
7:   for  $i \leftarrow 1, 2, 3$  do
8:      $M_i \leftarrow$  Train( $l_i$ )
9:   end for
10:  for  $i \leftarrow 1, 2, 3$ , do
11:     $l_i \leftarrow L$ 
12:    for  $j \leftarrow 1, n$  do
13:      if  $M_p(U_j) == M_q(U_j)$ 
14:        where  $p, q \neq i$  then
15:           $l_i \leftarrow l_i + \{(U_j, M_p(U_j))\}$ 
16:        end if
17:    end for
18:  end for
19: until no improvement in validation metrics

```

Model Architecture

Baseline: GloVe (Pennington et al., 2014) + Deep Averaging Net (Iyyer et al., 2015)

Final: BERT (Devlin et al., 2018) + CNN (Kim et al., 2014)



Results

Models/Experiments	Subtask - A	Subtask - B
Organizer Baseline	26.80	73.21
DAN + GloVe	38.84 ± 3.10	56.35 ± 4.71
DAN + BERT	60.82 ± 3.99	70.49 ± 4.09
CNN + BERT	64.81 ± 4.86	64.31 ± 6.72
CNN + BERT w/o Upsampling	70.58 ± 4.24	58.66 ± 7.79
CNN + BERT + Tritrain (Test set)	66.81 ± 1.90	82.19 ± 1.03
CNN + BERT + Tritrain (Yelp)	NA	81.98 ± 2.05

Table 1: F1-scores of different models/experiments
Confidence interval over 5 seeds.
DAN – Deep Averaging Network

Subtask	Model A	Model B	p-value
A	DAN + glove (Baseline)	DAN + BERT	≈ 0
A	DAN + BERT	CNN + BERT	0.046
B	CNN + BERT	CNN + BERT + Tritrain (Test set)	3.25e-08

Table 2: Pairwise comparison of various models using the McNemar’s Test
 $p \leq 0.05$ indicates a significant difference between the model performance.

References

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