

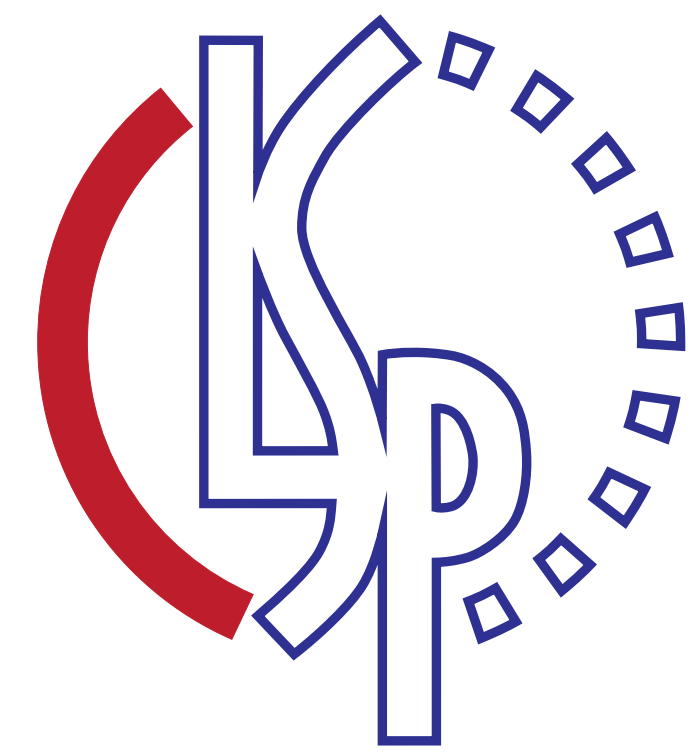


Regularized Training Objective for Continued Training for Domain Adaption in Neural Machine Translation

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Abstract

In supervised domain adaptation—where a large out-of-domain corpus and a smaller in-domain corpus are available for training—standard practice is to initialize with a model trained on out-of-domain data, and then *continue training* on in-domain data. We add an auxiliary term to the training objective during continued training that minimizes cross entropy between the model’s output distribution and that of the out-of-domain model to prevent the model from differing too much from the original out-of-domain model. We perform experiments on EMEA (descriptions of medicines) and TED (rehearsed presentations), initialized from a general domain (WMT) model. Our method shows improvements over standard continued training by up to 1.5 BLEU.

Method

- 1) Train a model until convergence on **out-of-domain** bitext using \mathcal{L}_{NLL} as the training objective (standard NMT loss; minimizes cross entropy between **gold label** and model output distribution)

$$\mathcal{L}_{\text{NLL}}(\theta) = - \sum_{v \in \mathcal{V}} (\mathbb{1}\{y_i = v\} \times \log p(y_i = v | x; \theta; y_{j < i}))$$

- 2) Initialize a new model with the final parameters of Step 1

- 3) Train this model (from Step 2) until convergence on **in-domain** bitext

- Standard continued training uses \mathcal{L}_{NLL}
- We add regularization term, \mathcal{L}_{reg} , to the loss to also minimize cross entropy between the model’s output distribution and that of the **out-of-domain** model
- This aims to prevent the model from differing too much from the original out-of-domain model

$$\mathcal{L}_{\text{reg}}(\theta) = - \sum_{v \in \mathcal{V}} (p_{\text{aux}}(y_i = v | x; \theta_{\text{aux}}; y_{j < i}) \times \log p(y_i = v | x; \theta; y_{j < i}))$$

- Our training objective for regularized continued training is the interpolation of \mathcal{L}_{NLL} and \mathcal{L}_{reg} :

$$\mathcal{L}(\theta) = (1 - \alpha) \mathcal{L}_{\text{NLL}}(\theta) + \alpha \mathcal{L}_{\text{reg}}(\theta)$$

Experiment

Data

- **Out-of-domain** data:
 - WMT17 (Europarl, News Commentary, Common Crawl, EU Press Releases)
 - ~6 million sents
- **In-domain** data:
 - Ted Talks (~150,000 sents)
 - EMEA – medical descriptions. (~1 million sents)
 - Also subselect small in-domain corpora of 2000 sentences per domain

NMT settings

- OpenNMT-py
- RNN encoder-decoder with attention
- BPE trained on out-of-domain text
- Re-set learning parameters when switching to in-domain

Results

- Performance of each model on the two domains

training condition	De-En		En-De	
	EMEA-test	TED-test	EMEA-test	TED-test
out-of-domain	30.8	29.8	25.1	25.9
in-domain	43.2	31.4	37.0	25.1
continued-train w/o reg	48.5	36.4	41.0	30.8
continued-train w/ reg	49.3 (+0.8)	36.9 (+0.5)	42.5 (+1.5)	30.8 (+0.0)

- Performance of each model on two domains with 2k in-domain sents

training condition	De-En		En-De	
	EMEA-test	TED-test	EMEA-test	TED-test
out-of-domain	30.8	29.8	25.1	25.9
continued-train w/o reg	34.3	33.4	30	28.1
continued-train w/ reg	35.2 (+0.9)	33.6 (+0.2)	30.2 (+0.2)	28.4 (+0.3)

Analysis

Is the additional training objective transferring general knowledge to the in-domain model?

- Yes! It helps even when we use it without continued training

training condition	De-En		En-De	
	EMEA-test	TED-test	EMEA-test	TED-test
out-of-domain	30.8	29.8	25.1	25.9
in-domain	43.2	31.4	37.0	25.1
in-domain w/ reg	45.5 (+2.3)	31.2 (+0.2)	38.8 (+1.8)	26.0 (+0.9)

- However, this does not compare to the performance of continued training, which is needed for competitive results
- This regularization term is an easy addition to boost continued training performance

Why does EMEA show larger improvements?

Possible explanations:

- EMEA has a lower OOV rate on the in-domain set
- TED has a lower OOV rate on the out-of-domain set
- TED is surprisingly similar to Europarl

