





DOMAIN ADAPTATION FOR SPEECH RECOGNITION THROUGH SEMI-SUPERVISED LEARNING

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Introduction

Semi-Supervised Learning is a type of machine learning that makes use of unlabeled data for training to improve accuracy, and has been shown to work in Automatic Speech Recognition^[1].

Domain Adaptation is the process of modifying a model trained on data from a specific source domain to improve performance on a target domain.

Our goal is to find the smallest quantity of out-of-domain speech data to train a speech recognition system whose predictions on unlabeled in-domain data improve accuracy during semi-supervised learning.

Motivation

The Multilingual Computing and Analytics Branch at ARL has speech-to-speech devices deployed with soldiers in noisy, conversational environments.

Most speech data available in low-resource languages is clean audio from parliamentary proceedings or TV news

A method to train low-resource, robust ASR models for everyday speech would benefit most ASR applications

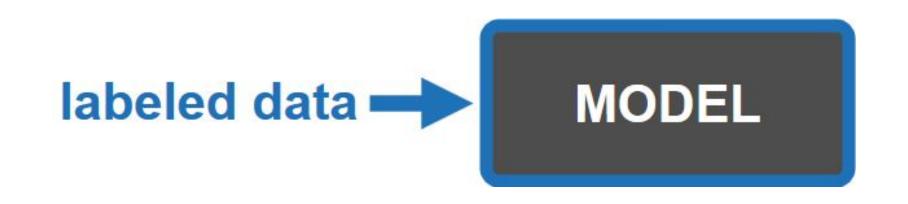
Data

We use two very common English ASR corpora, Wall Street Journal (WSJ) and Switchboard (SWBD)

| speech | domain | | labeled/ transcribed |
|------------------------|---------------|----------------------------------|-------------------------|
| Wall Street Journal | out-of-domain | edited news clean | yes |
| Switchboard | in-domain | conversational phone noisy | no |

Approach

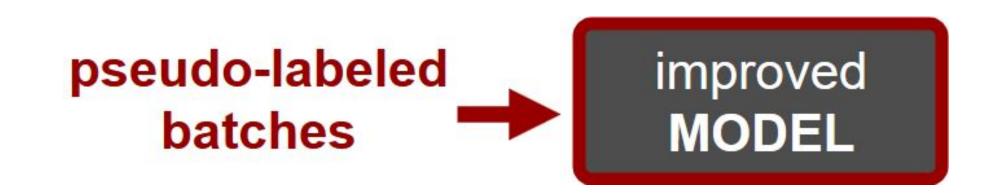
- 1. Prepare the data. Split the out-of-domain WSJ training data into subsets
- **2. Train a model.** Using Kaldi, train an LF-MMI chain model^[2] on each of the **WSJ** training subsets to get split1, split2, split3, etc.



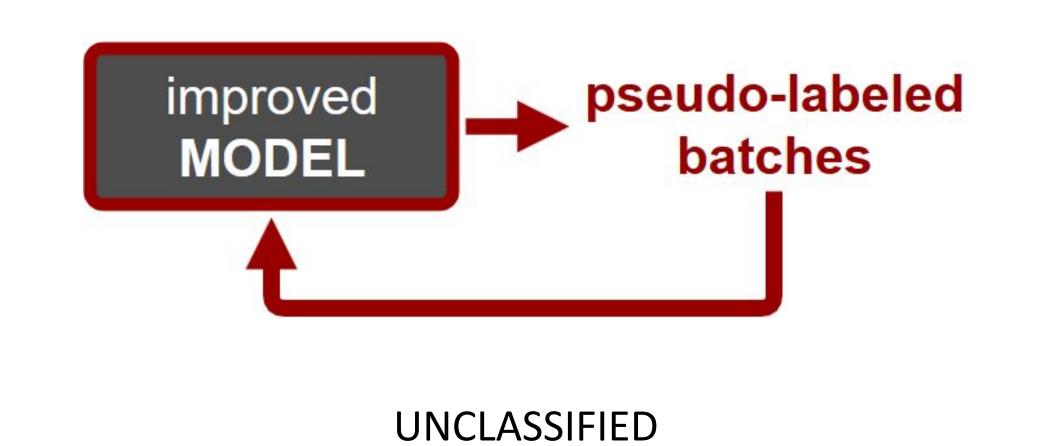
3. Assign pseudo-labels. Use each split's model to assign pseudo-labels to a batch of the unlabeled SWBD data



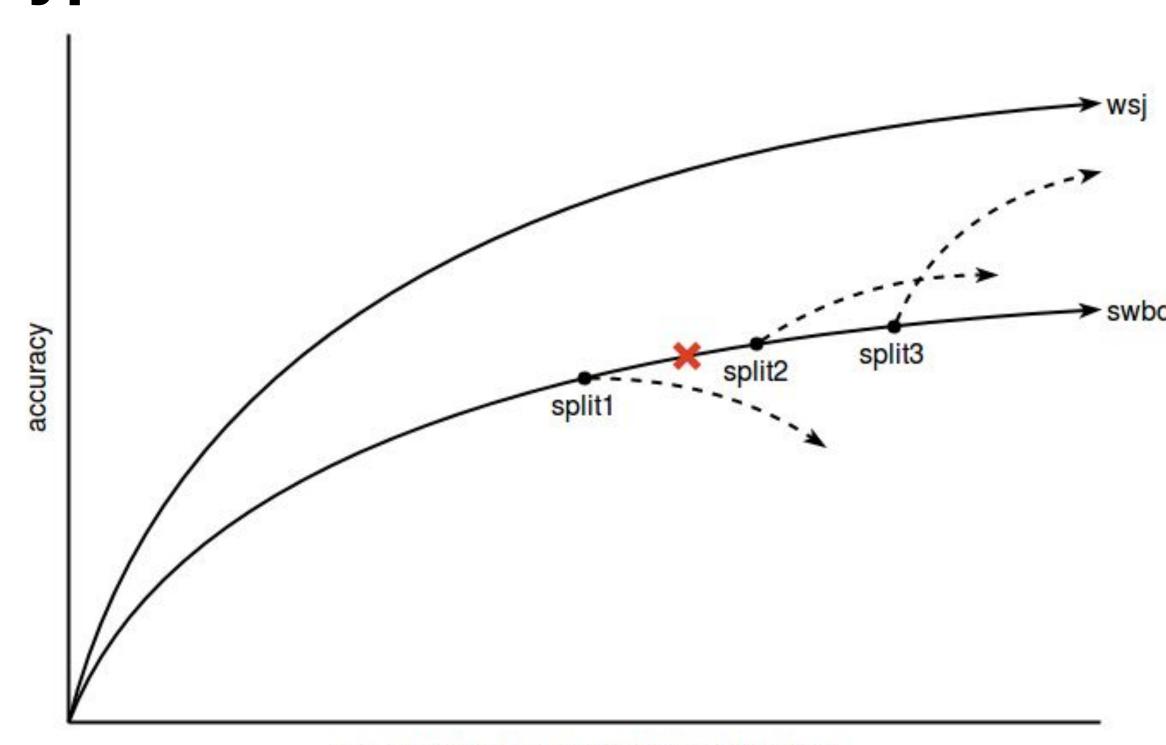
4. Train improved model. Continue to train the model on the pseudo-labeled **SWBD** batch to get an improved model



5. Repeat. Return to step 3 with improved model and incorporate another **SWBD** batch



Hypothesized Results



quantity of out-of-domain (wsj) train data

Results

Baseline Word Error Rates for splits prior to semi-supervised learning

| wsj training utterances | wsj test set | swbd test set |
|----------------------------|--------------|------------------|
| 5k | 11.67 | 94.76 |
| 10k | 9.03 | 86.95 |
| 15k | 7.60 | 85.98 |
| 20k | 7.23 | 83.74 |
| 25k | 7.20 | 72.96 |
| 30k | 7.03 | 79.91 |

Future Work

- 1. Test with different languages and different domains
- 2. Experiment with different language models
- 3. Investigate different neural architectures

References

- [1] Manohar, V., Hadian, H., Povey, D., & Khudanpur, S. (2018). Semi-Supervised Training of Acoustic Models Using Lattice-Free MMI. 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). doi:10.1109/icassp.2018.8462331
- [2] Povey, D., Peddinti, V., Galvez, D., Ghahremani, P., Manohar, V., Na, X., . . . Khudanpur, S. (2016). Purely Sequence-Trained Neural Networks for ASR Based on Lattice-Free MMI. Interspeech 2016. doi:10.21437/interspeech.2016-595