A TRANSFER LEARNING APPROACH FOR PRONUNCIATION SCORING

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PRONUNCIATION SCORING

Given a phrase uttered by a language learner, return a pronunciation quality score for each phone.

- Challenging task with room for improvement.
- Standard systems use models trained for automatic speech recognition (ASR) with native data only.
- Better performance using systems trained specifically for the task using native data.
- Datasets labelled for the task are scarce and usually small.

NATIVE DATA

- Rely on ASR technology to generate native models.
- Measures similarity between student's speech and native sounding speech.

NATIVE + NONNATIVE DATA

- Use non-native data with pronunciation quality labels.
- Directly trained to distinguish correctly from incorrectly pronounced segments.
- Variety of input features and classifiers.

TRANSFER LEARNING

- DNNs for pronunciation scoring show improvements over traditional methods of both groups
- Rely on transfer learning to mitigate data scarcity

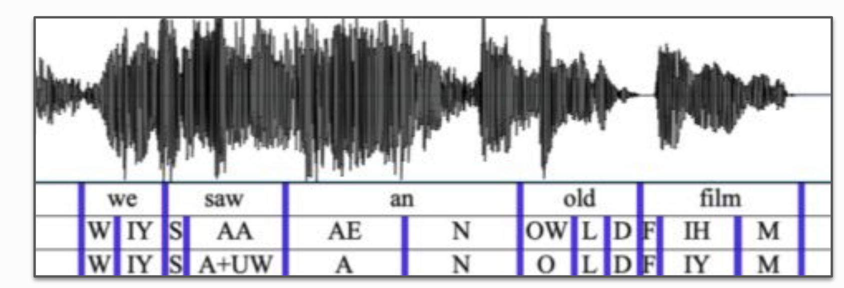
CONTRIBUTIONS

- Finetune the ASR model to the task of pronunciation scoring.
- Explore 2 different fine-tuning approaches and 6 design choices.
- Propose a loss function that compensates for inherent imbalance across phones and classes present in pronunciation scoring datasets.
- Measure performance using an alternative cost function designed to encourage low false correction rates.
- Share dataset and code to replicate the results at:

https://github.com/MarceloSancinetti/epa-gop-pykaldi

DATABASE

- 3200 nonnative English phrases by 50 speakers from Argentina.
- Manually annotated at detailed phonetic level using ARPAbet symbols.
- Correctly- and incorrectly-pronounced labels are assigned to each of the target phones determined by the forced-alignment system



BASELINE METHOD: GOP

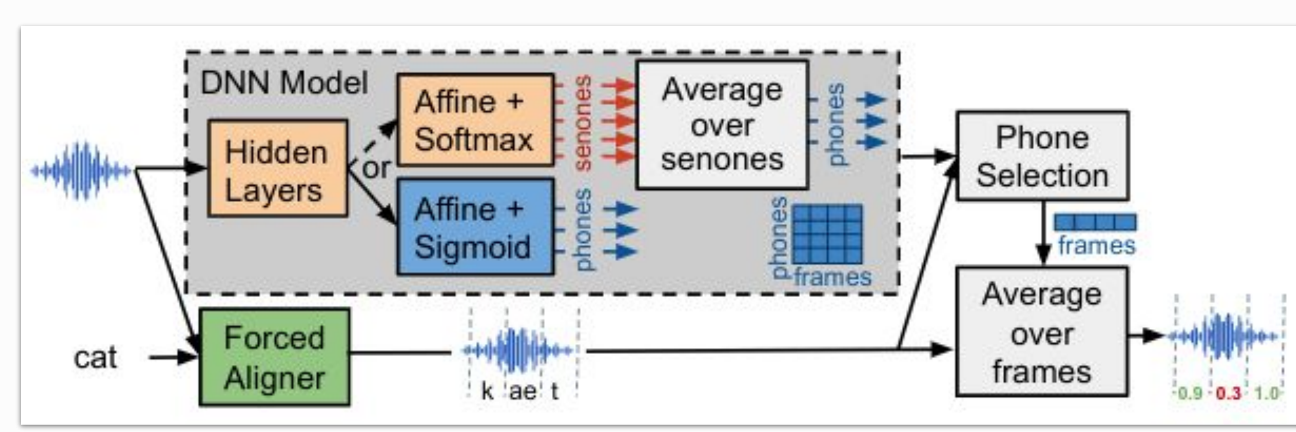
- **GOP scores:** for each phone, the averaged posterior probability of the target phone for each frame.
- Computed using the outputs of a senone acoustic model.

$$GOP(p) = -\frac{1}{D}\sum_{t=T}^{T+D-1} \log P_t(p|O)$$

- Start and end frames are obtained from forced alignment.

- Official Kaldi recipe reproduced in Pykaldi
- Features: 40-dimensional MFCCs + I-vectors.
- Acoustic model: TDNN-F trained on Librispeech (960 hours) (decoding and forced alignment)
- 17 layers + output layer of size 6024 senones + softmax

TOP BRANCH - GOP



BOTTOM BRANCH- GOP-FT

PROPOSED METHOD: GOP-FT

- Replace baseline output layer with a layer that predicts per phone per frame probability of correctly pronounced
- **GOP-FT scores:** for each frame the probability of being correctly pronounced for the target phone in that frame. Then average over the frames.
- **Weighted cross-entropy loss:**

$$L = -\sum_{p\in P}\sum_{y\in Y} w_{py} \sum_{t\in T_{py}} y_t \log \hat{y}_t + (1-y_t)\log(1-\hat{y}_t)$$

w_{py} adjust the influence of the samples from each phone and class.

Flat Weights:	*Zero Weight:*	Balanced
$w_{py} = 1$	$w_{py} = 0$	$w_{py} = 1/N_{py}$

- Features: 40-dimensional MFCCs + I-vectors.
- Acoustic model: Kaldi's TDNN-F trained on Librispeech (960 hours) ported to Pytorch (decoding and forced alignment)
- 17 layers + affine output layer of size 39 + sigmoid

EXPERIMENTS

- **LayO:** only the new output layer is trained, keeping all other parameters frozen at their pre-trained values.
- **LayO+1:** the last hidden layer is also trained.
- **BN**: batch-normalization in the output layer.
- **DO**: dropout in all layers.
- **Bal**: the loss with balanced weights is used in training.

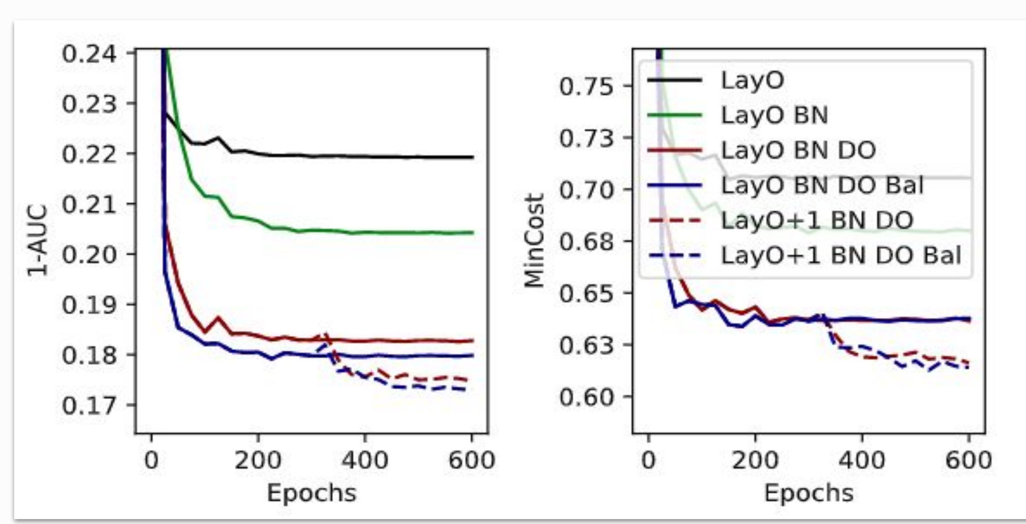
COST FUNCTION

- Allows to control false negatives / useful for pedagogical reasons

Cost = 0.5 FPR + FNR

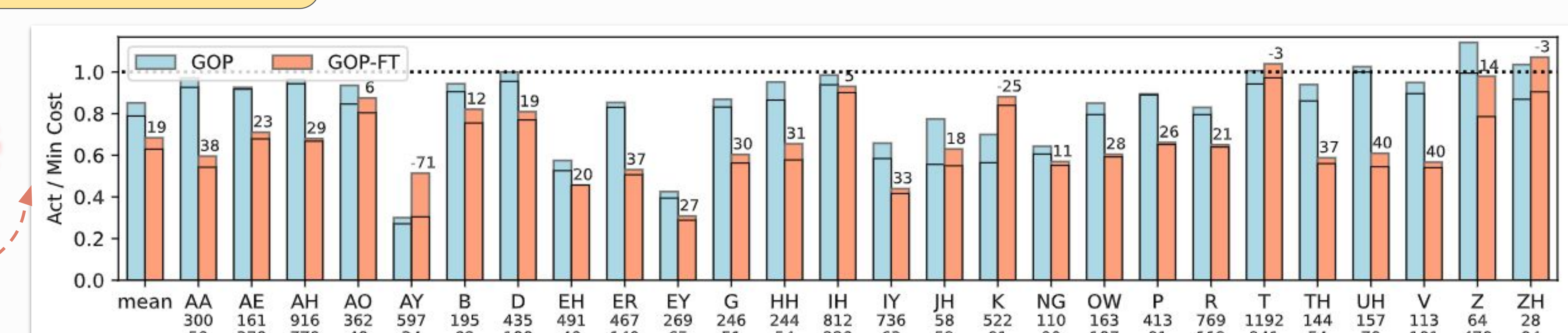
- Allows to to see the effect of the threshold selection.
- **MinCost**: computed on test data / **ActCost:** computed on dev data.

RESULTS / CONCLUSIONS



- Average 1-AUC and MinCost (phones with more than 50 samples of each class for the development data)
- GOP system has 1-AUC of 0.286 and MinCost of 0.801.
- **Best configuration: LayO+1 BN DO BAL**

The bars with a solid black line show the MinCost. The top bar are the ActCost.



- ActCost is within 10% of the MinCost for most phones (thresholds on development speakers generalize well to the unseen speakers).
- Average FNR rate is 10% (GOP) and 13% (GOP-FT). Acceptable level for real use scenarios.
- Average FPR is 64% (GOP) and 41% (GOP-FT). 23% relative improvement from fine-tuning approach.