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Summary

We present findings on how representation learning on large unlabeled speech corpora can be beneficially utilized for speech emotion recognition (SER). Evaluation is done by means of within- and cross-corpus testing.

Main findings:

- Integrating representations learned by unsupervised autoencoder improves emotion classification
- Autoencoder representations bear emotional informa**tion** (especially arousal dimension)
- Consistent improvements for within- and cross-corpus evaluation

Methods

- Train time-recurrent sequence-to-sequence autoencoder on spectrograms from large speech corpus (auDeep toolkit [1])
- Generate latent representations for emotional speech (2)
- Train attentive convolutional neural network (ACNN) [2] with **3**) those representations as additional feature vector



Improving Speech Emotion Recognition with Unsupervised Representation Learning on Unlabeled Speech

Speech Corpora

- IEMOCAP [3] 5,531 utterances from 10 speakers,
 - classes {angry, happy, neutral, sad}
- MSP-IMPROV [4] (only for evaluation) 7,798 utterances from 12 speakers, same 4 classes
- Tedlium r2 [5] 207 hours (92,973 utterances)
- Librispeech [6] 100 hours subset (28,539 utterances)

Experimental Results

Baseline

- ACNN without additional representations
- 5-fold cross validation (speaker-independent) for IEMOCAP

Autoencoder (AE) training on 4 datasets

- a) 'Control condition': AE trained on IEMOCAP itself (respectively MSP-IMPROV) – no additional data source
- b) 'small Tedlium': AE trained on subset of Tedlium (400 Ted talks, 25,303 segments)
- c) 'Librispeech': AE trained on 100 hours Librispeech data
- d) 'full Tedlium': AE trained on 207 hours of speech

Unweighted average recall (UAR), averaged over 10 runs of the experiments for each setting

	IEMOCAP	MSP-
		(cross
Baseline	58.03	4
a) Control	58.07	4
b) small Ted	58.85	4
c) Librispeech	59.05	4
d) full Ted	59.54	4

 \rightarrow Consistent improvements when adding representations generated by different AE models b), c), and d)

Visualization of Speech Representations





- ACNN: angry and sad separated to certain extend; high-variance cluster for happy
- ACNN: much more discriminativ
- AE: similar patterns despite no e
- $\bullet \rightarrow AE$ implicitly learns to separat
- Both representations are invaria tity (no separable clusters found

Selected References

- [1] Michael Freitag, Shahin Amiriparian, et al., "audeep: Unsupervised learning of representations from audio with deep recurrent neural networks," The Journal of Machine Learning Research, vol. 18, no. 1, 2017.
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- [3] Carlos Busso, Murtaza Bulut, et al., "lemocap: Interactive emotional dyadic motion capture database," Language resources and evaluation, vol. 42, no. 4, 2008.
- [4] Carlos Busso, Srinivas Parthasarathy, et al., "Mspimprov: An acted corpus of dyadic interactions to study emotion perception," IEEE Transactions on Affective *Computing*, vol. 8, no. 1, 2017.
- [5] Anthony Rousseau, Paul Deléglise, and Yannick Esteve, "Enhancing the ted-lium corpus with selected data for language modeling and more ted talks.," in Proc. of the Ninth International Conference on Language Resources and Evaluation (LREC-2014), 2014.



IMPROV

- s-corpus)
- 2.99
- 2.37
- 5.21
- 4.82
- 5.76

t-SNE visualizations of last hidden layer of the ACNN for IEMOCAP

t-SNE visualizations of the AE representations for IEMOCAP (AE trained on full Tedlium, no emotion information involved in training)

e for arousal than for valence
emotion labels are involved
te low and high arousal
ant to speaker sex and speaker iden-
d in visualizations)

:) f	[6]	Vassil Panayotov, Guoguo Chen, et al., "Librispeech: an asr corpus based on public domain audio books," in Proc. of International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2015.
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-	[8]	Sefik Emre Eskimez, Zhiyao Duan, and Wendi Heinzel- man, "Unsupervised learning approach to feature anal- ysis for automatic speech emotion recognition," in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018.
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