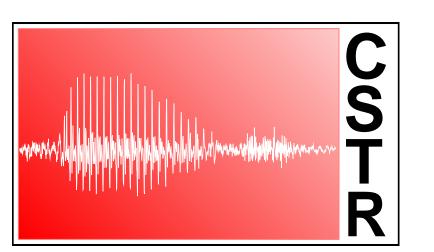


Engineering and Physical Sciences Research Council

# A learned emotion space for emotion recognition and emotive speech synthesis



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### Introduction

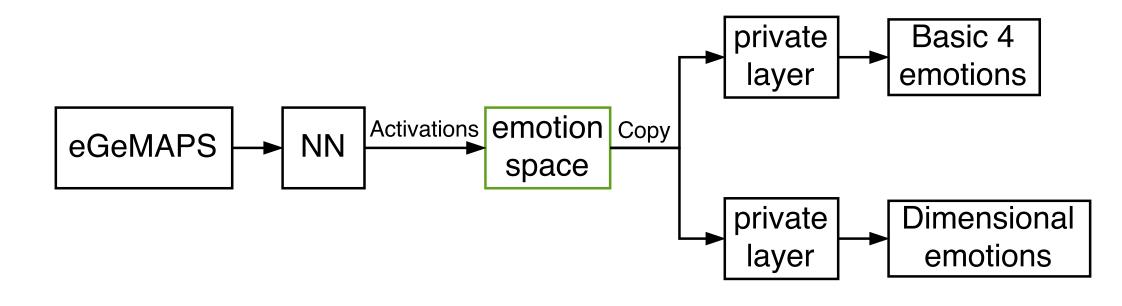
Most emotion recognition research focusses on two descriptions of emotion, both of these have flaws;

• Categorical (happy, sad, angry, neutral) Too coarse to describe real emotion

#### **Emotion space**

### **Emotive speech synthesis**

- Multi-task learning (MTL) to train emotion space
- Emotion space is the final shared layer's activations



• DNN synthesis using Merlin toolkit [7]

• Style adaptation using **auxiliary features** 

• eGeMAPS - 88 acoustic parameters from waveform

- Dimensional (arousal, valence, dominance) Open to interpretation  $\rightarrow$  **unreliable** annotations We address this in three stages;
- Learning an abstract **emotion space** with MTL
- Using **stimulation** to improve interpretability
- Evaluation using expressive SPSS voices

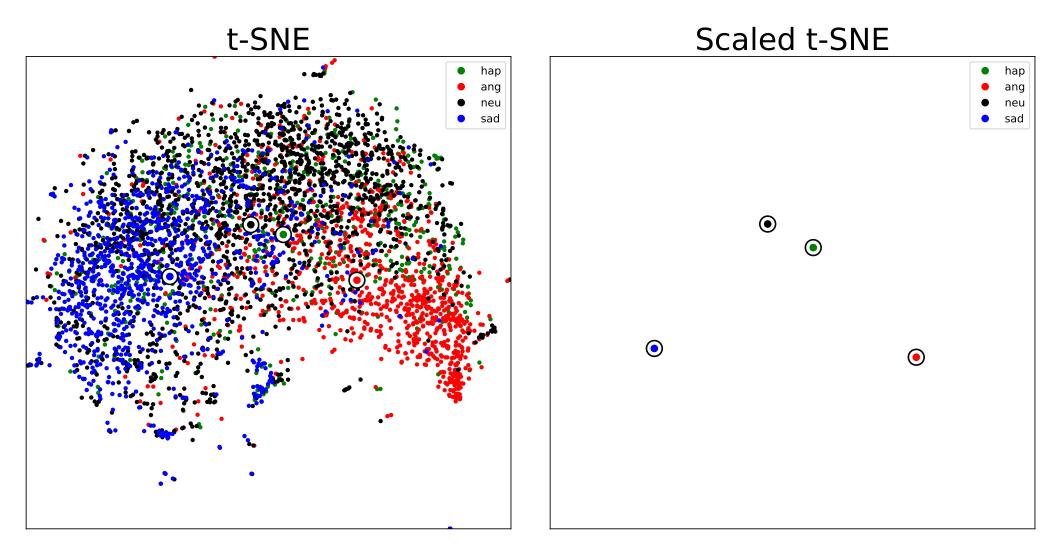
#### Datasets

- IEMOCAP dataset [1] contains 12 hours of scripted and improvised dyadic interactions from **10 actors**. Each utterance has **categorical and dimensional** labels from 3 annotators
- **Usborne** children's audiobook dataset, used in Blizzard 2017 [2], contains 6.5 hours of expressive speech from a **British female speaker**

Figure 2: MTL architecture showing emotion space

### Stimulation [6]

• Regularisation method that encourages high activations surrounding points in a prior map • Prior map is a layout of classes on a unit-grid • t-SNE embedding used as prior map (Figure 3b) Stimulation improves interpretability of emotion



- Dimensional 3-dimensional emotion description • eGrid - emotion space, stimulated in a 16 x 16 grid
- Categorical 4-class emotion description
- Non-emotive no auxiliary features

Table 2: Objective results of trained DNN synthesis voices

#### **Objective metric** $\log F_0$ VUV MCD BAP (RMSE) (error %) (dB)(dB)eGeMAPS 5.631 0.314 44.356 14.254**Dimensional** 5.850 0.327 14.864 50.439 15.211**eGrid** 5.825 0.327 51.420 **Categorical** 5.820 0.324 14.493 52.372 **Non-emotive** 5.845 0.329 14.76852.846

#### Listening test

## **Emotion recognition**

Standard categorical emotion recognition on IEMO-CAP. Using narrowband spectrogram, or the minimalistic acoustic parameter set, eGeMAPS [3]

Table 1: Performance classifying; happy, sad, angry, neutral

Model	Inputs	Accuracy
Random	N/A	24.14%
Most common	N/A	33.00%
LSTM	eGeMAPS LLDs	43.17%
TD-CNN	Spectrogram	58.94%
DNN	eGeMAPS functionals	72.77%
RNN-ELM $[4]$	MFCCs, $F_0$ , VUV, zero-crossings	63.89%
CNN-MKL [5]	ComParE 2016, video, word2vec	$\mathbf{76.85\%}$

• LSTM - recurrent neural network; ongoing work • TD-CNN - time-distributed CNN; ongoing work • DNN; for 4-class speech-only IEMOCAP, result is

(a) t-SNE embedding (b) Scaled class means Figure 3: t-SNE embedding of eGeMAPS features for IEMOCAP

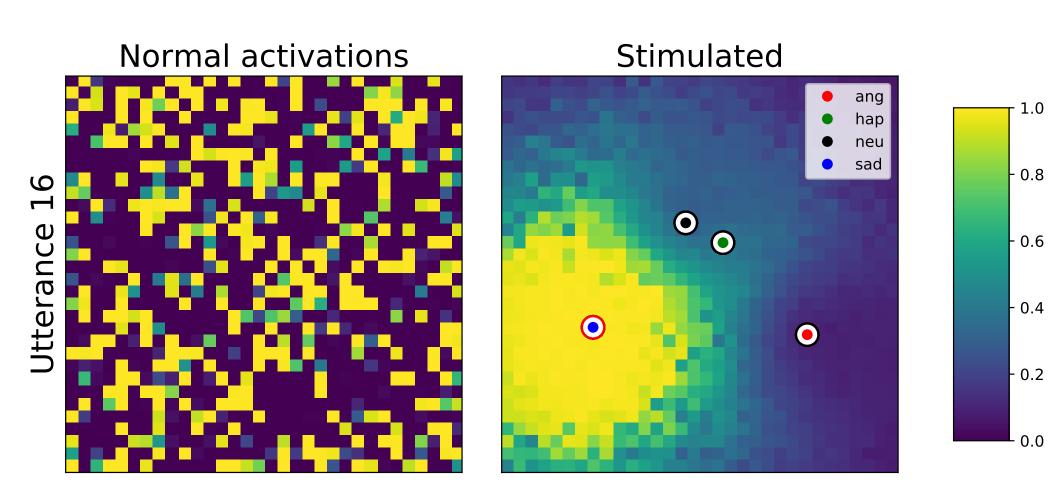


Figure 4: Visualisation of activations without & with stimulation

#### **Cross-corpus** prediction

• MUSHRA listening test, 16 screens, 20 participants

• Copy synthesis reference: 100 rating for all samples

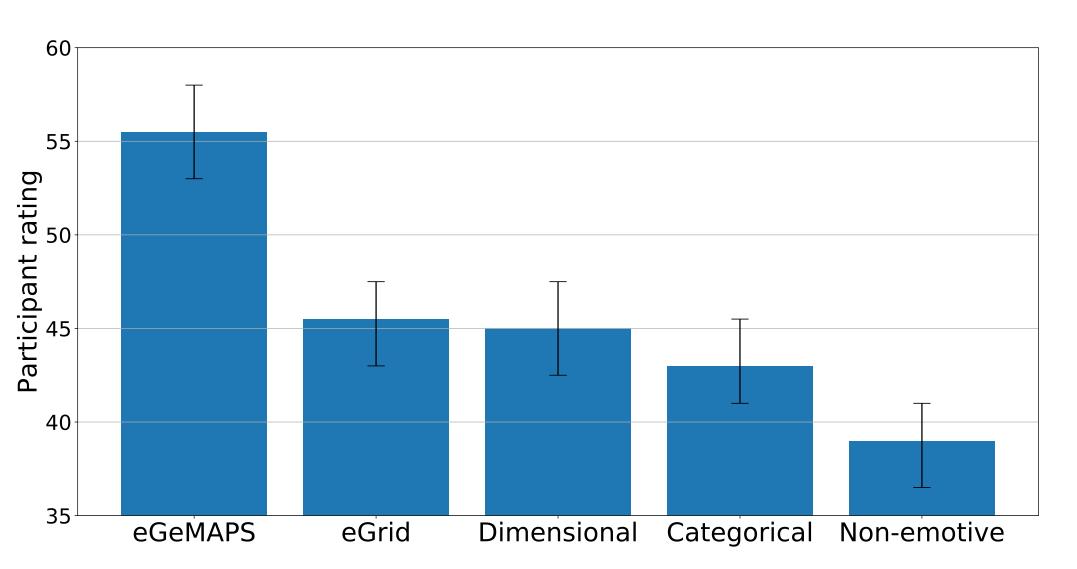
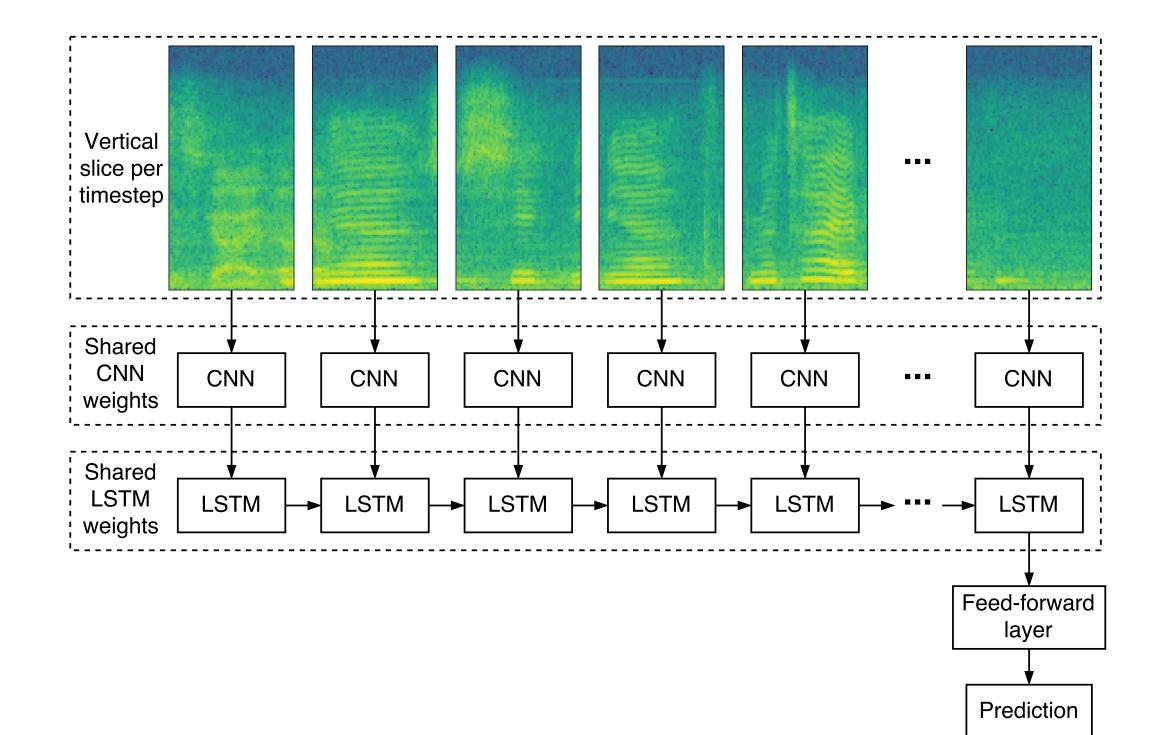


Figure 6: Ranksum test. Median rating & 95% confidence interval

#### Conclusion

• To mitigate issues with existing emotion descriptions, we learn an emotion space using MTL • Stimulation is added to improve interpretability

#### **state-of-the-art**, dependent on the test set split



Create auxiliary features for SPSS style adaptation;

- Use recognition model trained on IEMOCAP
- From Usborne data, **predict**;

emotion space, categorical and dimensional labels

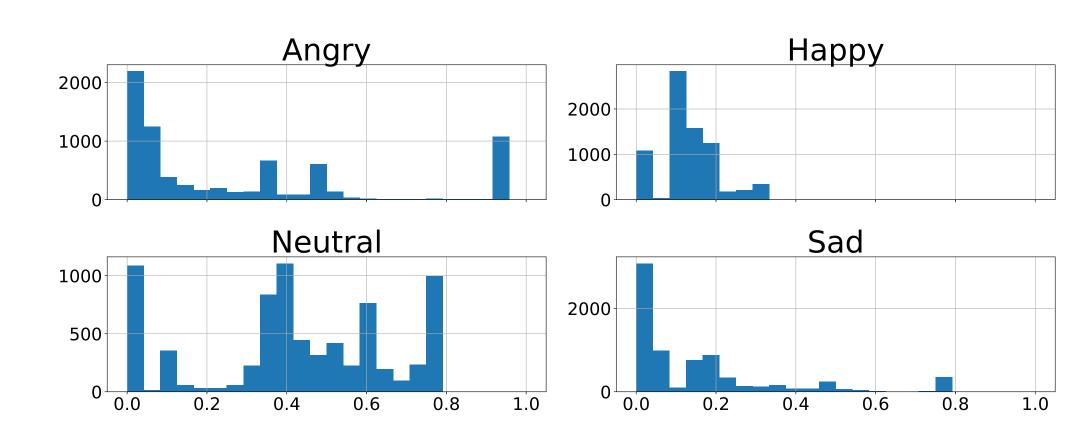


Figure 1: Time-distributed CNN architecture

Figure 5: Distribution of Usborne categorical emotion predictions

• Evaluation is performed with a perceptual test

#### References

[1] Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeannette N Chang, Sungbok Lee, and Shrikanth S Narayanan. IEMOCAP: Interactive emotional dyadic motion capture database, 2008. [2] Simon King and Vasilis Karaiskos. The blizzard challenge 2016. [3] Florian Eyben, Klaus R Scherer, Björn W Schuller, Johan Sundberg, Elisabeth André, Carlos Busso, Laurence Y Devillers, Julien Epps, Petri Laukka, Shrikanth S Narayanan, et al. The geneva minimalistic acoustic parameter set (GeMAPS) for voice research and affective computing, 2016.[4] Jinkyu Lee and Ivan Tashev. High-level feature representation using recurrent neural network for speech emotion recognition, 2015. [5] Soujanya Poria, Iti Chaturvedi, Erik Cambria, and Amir Hussain. Convolutional MKL based multimodal emotion recognition and sentiment analysis, 2016 [6] Shawn Tan, Khe Chai Sim, and Mark Gales. Improving the interpretability of deep neural networks with stimulated learning, 2015. [7] Zhizheng Wu, Oliver Watts, and Simon King. Merlin: An open source neural network speech synthesis system, 2016.