DEEP ENCODED LINGUISTIC AND ACOUSTIC CUES FOR ATTENTION BASED END TO END SPEECH EMOTION RECOGNITION

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Speech Emotion Recognition (SER) has several applications:
- man-machine interactions
- human health assistance
- call center analytics etc.
Introduction

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  - man-machine interactions
  - human health assistance
  - call center analytics etc.

- Developments in deep learning especially in terms of,
  - data augmentation
  - better feature extractors
  - cross-domain knowledge transfer
  have significantly impacted SER.
Introduction

• Speech Emotion Recognition (SER) has several applications
  • man-machine interactions
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  • call center analytics etc.

• Developments in deep learning especially in terms of,
  • data augmentation
  • better feature extractors
  • cross-domain knowledge transfer
    have significantly impacted SER.

• Can be further improved by exploiting,
  ➢ Acoustic information : Spectrograms from raw audio and glottal source signals
  ➢ Linguistic information : Text, Phoneme sequences, intermediate DNN representations
Related Work

Two directions:

➢ Use complex hand-crafted features (ex: OpenSMILE feature set)
➢ Deep modelling with conventional raw audio spectrograms
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Transferring knowledge within tasks/datasets\(^1\)

- In Deep networks, initial layers ➔ low-level features
  - final layers ➔ high-level features
- Transfer learning ➔ share knowledge across datasets and tasks.

\(^1\) [https://haythamfayek.com/assets/talks/Fayek_neurips18.pdf](https://haythamfayek.com/assets/talks/Fayek_neurips18.pdf)
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“Low-level features are more generic and easier to transfer from one task to another”
Could there be exceptions?
Related Work

Jointly learning supplementary tasks \[2\]

- Uncertainty about most relevant and robust features/layers

- Progressive network: training ASR and SER tasks jointly

- ASR representations show improved performance mainly due to the robustness to speaker and condition variations.

\[2\] https://www.aclweb.org/anthology/I17-1043.pdf
Jointly learning supplementary tasks \cite{ICASSP2020}

- Uncertainty about most relevant and robust features/layers
- Progressive network: training ASR and SER tasks jointly
- ASR representations show improved performance mainly due to the robustness to speaker and condition variations.

Key Takeaways from related work:
- Influence of linguistic knowledge in spoken utterances for SER task still remains unexplored.
- Selection of intermediate ASR layers needs to be studied thoroughly.

\cite{ICASSP2020} \url{https://www.aclweb.org/anthology/I17-1043.pdf}
Proposed System

Representative features

**Acoustic features** : **Mel-spectrogram**

- Sampling rate = 16 kHz
- Frame duration = 25 msec
- Length of FFT window = 2048
- Hop length = 400 samples
- Number of bins on mel-scale = 128

Concatenate $\Delta$ and $\Delta-\Delta$ for the mel-spectrogram.
Representative features

Deep encoded Linguistic features: DeepSpeech ASR \[^{[3]}\]

Note: Layers closer to output capture the linguistic content of speech while the layers close to input capture the acoustic content.\[^{[4]}\]

Representative features


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Can we get linguistic context of embedded emotion in the spoken utterance?

Visualization of activations from different layers of DeepSpeech model, for the same utterance spoken in different emotions. Columns represent the 6 layers and rows represent emotions. \textit{anger}; \textit{fearful}; \textit{happy}; \textit{calm}; \textit{sad}.

- $1^{\text{st}}$, $2^{\text{nd}}$ and $5^{\text{th}}$ layers show least correlation across the rows (emotions).
- Lesser correlation in $1^{\text{st}}$ and $2^{\text{nd}}$ layer is due to variations in speaker, gender etc. \cite{4}
- We use the output from the $5^{\text{th}}$ layer for getting the linguistic context for the SER task.

\textbf{Representative features}
**Proposed architecture**

**Encoder:**
- 2 layers of 1-D convolutions.
  - Helps to learn temporal context between adjacent frames.
- 1-D convolution layer
  - Batch normalization layer
  - ReLU activation

**Decoder:**
- Multi-head self attention layer
  - Average pooling
  - 2 feedforward dense layers.

**Output:**
Softmax distribution over individual emotions.

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Deep encoded Linguistic and Acoustic cues for SER
Multi-head Self Attention

- Let $E$ be the output of the encoder block
- $W_i$ are trainable weight matrices
- $d_i$ is the dimension
- $A_i$: Attention weight of a single head
- $A_{MH}$: Final multi-head self attention
- $h$: total number of heads

\[
A_i = \text{softmax} \left( \frac{Q_i K_i^T}{\sqrt{d_K}} \right) V_i \quad \forall i \in \{1, 2, \ldots, h\}
\]

\[
Q = EW_Q, \quad K = EW_K, \quad V = EW_V
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\[
A_{MH} = (A_1 \| A_2 \| \cdots \| A_h) W_E
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Context, \( C = E + A_{MH} \)
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Context, $C = E + A_{MH}$
Experiments

- Dataset: IEMOCAP\textsuperscript{[5]}
  - Recording setups:
  - Categorical Emotion classes:

- Model configurations:

\textsuperscript{[5]} Carlos Busso, IEMOCAP: Interactive Emotional Dyadic Motion Capture database,” Language resources and evaluation, 2008.
## Results

Experiments with improvised recordings

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<th>Model (Input features)</th>
<th>Weighted Acc., WA</th>
<th>Unweighted Acc., UA</th>
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**Observation:**
- Improvement using only Acoustic features ✓
- Improvement using Linguistic features (or +Acoustic features) ✗

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What if there is **linguistic context embedded** within the samples?
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Experiments with scripted recordings

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➢ 7.64% improvement compared to “only acoustic features” as input.
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What if the data itself has a combination of both scripted and improvised speech?
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Experiments with scripted + improvised recordings

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**Reasoning:**

- Class imbalance in the combined scenario plays important role
  - Model -1 achieves best WA but very low UA
- Fusion of linguistic information + acoustic features -> + 2.89% in UA
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But, is the self-attention module actually helping?
Model learns the acoustically significant frames and weighs them heavily during the formation of context.

Strong emphasis around the word “everything” makes it almost distinctive as anger emotion.

Not all heads contribute equally, most important and confident heads play a consistent role.

Attention weights \( A_i = \text{softmax} \left( \frac{Q_i K_i^T}{\sqrt{d_K}} \right) V_i \) for each attention head.

- **T**: timesteps
- **True emotion**: anger

**Discussion**
Conclusion

• Proposed an End-to-End model for an improved SER system using self attention mechanism.
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- Less correlation of linguistic cues with the emotion than its acoustic counterpart in the improvised recordings.
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- Less correlation of linguistic cues with the emotion than its acoustic counterpart in the improvised recordings.

- Combination of linguistic and acoustic features gives an improvement of
  - 6.29% for only scripted
  - 2.86% for combined scenario indicating usefulness of our approach.
Thank You!

- Swapnil Bhosale
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