On the Correlation and Transferability of Features between Automatic Speech Recognition and Speech Emotion Recognition

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Outline

Introduction

Experimental Setup

Results

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Background

• The relationship between Automatic Speech Recognition (ASR) and Speech Emotion Recognition (SER) is ill-defined.

• Acoustic models in ASR utilise a few frames to recognise phonemes that are later decoded into a transcription.

  Acoustic models in SER require a larger number of frames to recognise emotions.

• Most work in ASR considers the presence of paralinguistics (e.g. Emotions) in speech a form of distortion.

  Improvement was reported in SER in the presence of a linguistic input.
Hybrid ASR-SER

Figure: A Hybrid ASR-SER System.

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Relation Between ASR and SER

- Deep learning is the state-of-the-art approach for ASR and SER.
- The relation between ASR and SER must be studied prior.
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We can study the relation between ASR and SER by studying the relation and relevance of the features learned in both tasks using transfer learning.
Related Work

- Deep neural networks tend to learn low-level features in initial layers and transition to high-level features in final layers.

- Yosinski et al. (2014) showed on a computer vision task that there is a correlation between the benefit of feature transfer and the distance between both tasks.

- Transfer Learning has been used in:
  - ASR: cross-language, speaker adaptation, etc.
  - SER: cross-corpus, music, etc.
Transfer Learning: ASR ↔ SER

Figure: Transfer Learning between ASR and SER.
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Data

• **ASR Data:**
  TIMIT: 630 speakers from 8 major American English dialects.
    • Training set: Complete set of 462 speakers without SA utterances.
    • Development Set: 50-speaker set.
    • Test Set: Core set of 24 speakers.

• **SER Data:**
  IEMOCAP: 10 speakers producing 12 hours of audiovisual recordings.
    • Classes: anger, happiness + excitement, neutral, sadness.
    • 8-Fold Leave-One-Speaker-Out (LOSO) cross-validation.
    • 2 Speakers left out as a validation set.
Preprocessing

• Preprocessing:
  • Speech analysed 25ms Hamming window with a stride of 10ms.
  • 40-coefficient Log Mel-scale Fourier-transform based filter banks.
  • Speaker-independent mean and variance normalisation with training subset.

• ASR Labels:
  • Force-aligned labels were obtained with a GMM-HMM system with MFCCs using the standard Kaldi recipe.

• SER Labels:
  • Frame labels were inherited from the parent utterance labels.
  • A VAD was then used to label silent and unvoiced frames and a Silence label was added as an extra class.
ConvNet Acoustic Model

Table: *Convolutional Neural Network Architecture.*

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<td>(l_2 = 1 \times 10^{-3})</td>
</tr>
<tr>
<td></td>
<td>BatchNorm</td>
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<td></td>
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<tr>
<td></td>
<td>ReLU</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Max Pooling</td>
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<td>Stride = 2</td>
</tr>
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<td>2</td>
<td>Convolution</td>
<td>128, 3 × 3</td>
<td>(l_2 = 1 \times 10^{-3})</td>
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<tr>
<td></td>
<td>ReLU</td>
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<td></td>
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<tr>
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<td>Max Pooling</td>
<td>2 × 2</td>
<td>Stride = 2</td>
</tr>
<tr>
<td>3</td>
<td>Fully-Connected</td>
<td>1024</td>
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<td></td>
<td>BatchNorm</td>
<td>-</td>
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<td></td>
<td>ReLU</td>
<td>-</td>
<td></td>
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<tr>
<td></td>
<td>Dropout</td>
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<tr>
<td></td>
<td>Softmax</td>
<td>-</td>
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</table>
System Architecture and Training

• ASR System:
  31 Frames + ConvNet Acoustic Model + 3-State HMM Bi-Gram LM.

• SER System:
  31 Frames + ConvNet Acoustic Model.

• Training:
  • Parameters were initialised from a Gaussian distribution with zero mean and $\sqrt{2/n}$ standard deviation.
  • Mini-batch SGD and RMSProp with respect to a CE cost function.
  • Validation set was used for early stopping.
  • Trained on a cluster of Tesla K40 GPUs.
Transfer Learning: ASR ↔ SER

Figure: Transfer Learning between ASR and SER.
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Transfer Learning: ASR $\leftrightarrow$ SER

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Learned Features

Figure: Learned Features from ASR (left) and SER (right).
Results: SER to ASR

Figure: Transfer Learning Performance from SER to ASR.
Results: SER to ASR

Table: Transfer Learning Performance SER to ASR.

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<td>Baseline</td>
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<td>30.62%</td>
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Results: ASR to SER

Figure: Transfer Learning Performance from ASR to SER.
Results: ASR to SER

Table: Transfer Learning Performance ASR to SER.

<table>
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<th>No. Constant Layers (I)</th>
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<th>UE</th>
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<td>Test</td>
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<td>46.37%</td>
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</tr>
<tr>
<td>0</td>
<td>45.26%</td>
<td>46.97%</td>
</tr>
</tbody>
</table>
Results

Figure: Transfer Learning Performance between ASR and SER.
Conclusion

- The relevance of features learned and information propagation in ConvNets between ASR and SER was studied using transfer learning.

- Results attested to the feasibility of transfer learning between both tasks.

- Initial layers in the network were more transferable between both tasks and the relevance of features decays gradually through deep layers.
Thank you
Questions & Discussion