Deep Neural Network for Speech Emotion Recognition
—A Study of Deep Learning—
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05.06.2014

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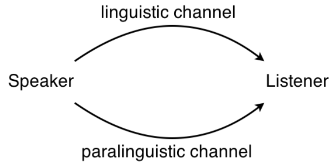
Motivation

Why speech emotion recognition

- Most current work focuses on speech processing based on linguistic information, e.g.: Skype Translator
- More natural human-machine interaction requires paralinguistic information such as age, gender, emotion.
- Speech Recognition / Speeker Identification / Emotion

Recognition



Deep Network Applications

- Handwriting Digit Recognition
- Image Recognition

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Recognition
Deep Network Applications
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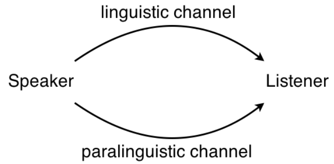

Deep Network Applications

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Deep Learning
└ Foundations
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Mel Frequency Cepstral Features

- short-term power spectrum
- mel-scale approximate human perception
- widely-used in speech recognition tasks

Transformation between Mel and Hertz scale

$$f_{mel} = 1125 \ \ln\left(1 + f_{Hz}/700\right) \quad (1)$$

$$f_{Hz} = 700 \left(\exp(f_{mel}/1125) - 1\right) \quad (2)$$

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Emotion Recognition Approaches
Traditional Approaches
- pre-selected features
- supervised training
- low-level features not appropriate for claasification
- shallow structure of classifiers
Deep Learning Approaches
- learning representations from high-dim data
- extracting appropriate features without hand-crafting
- low-level features are used to build high-level features as network gets deeper
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Computing net-activation

$$
\begin{aligned}
\underline{z}_k^{(l+1)} &= \mathbf{W}^{(l)}\underline{a}_k^{(l)} + \underline{b}^{(l)} \\
\underline{a}_k^{(l+1)} &= \underline{\mathit{\Phi}}\left(\underline{z}_k^{(l+1)}\right) \\
\underline{\hat{y}}_k &= \underline{a}_k^{(ol)}
\end{aligned}
$$

- Arbitrary non-linear mapping from $\underline{x}_k$ to $\underline{\hat{y}}_k$ possible
- Relation $N \Leftrightarrow$ Complexity
- Deep Architectures $(l\uparrow)$ more efficient than shallow ones $(l\downarrow, N_l\uparrow)$

Determining the parameters

Training objective

$$J(\mathbf{W}, \underline{b}) = \sum_{\forall k} \frac{1}{2} ||\underline{y}_k - \hat{\underline{y}}_k||^2 + \frac{\lambda}{2} \sum_{\forall l} ||\mathbf{W}^{(l)}||_F^2 \quad (3)$$

$$\mathbf{W}, \underline{b} = \arg\min_{\mathbf{W}, \underline{b}} J(\mathbf{W}, \underline{b}) \quad (4)$$

Numerical minimization

- Gradient calculation with Backpropagation
- Stochastic gradient descent
- **L**imited memory **B**royden-**F**letcher-**G**oldfarb-**S**hanno (L-BFGS)

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Problems
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  $\Rightarrow$ getting stuck in poor local minima
- Diffusion of gradients
- Large p small n problem $\Rightarrow$ overfitting

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Solutions
- Layerwise Pre-training
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Deep Learning
└Long Short Term Memory
 └Recurrent Neural Network
  └Recurrent Neural Network

Recurrent Neural Network
Concepts of RNN
- Same Structure as MLP but differs from feed-forward network, enabling nonlinear mapping.

$$h_t = \mathcal{H}(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$$
$$y_t = W_{hy}h_t + b_y$$

- Feedback connection between previous hidden units and current hidden units, enabling memory past hidden state.
- Potentially to model arbitary dynamic system.
- Trained with backpropagation through time (BPTT)

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tell me a story.

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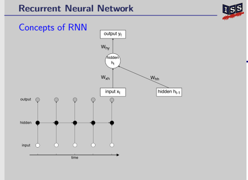

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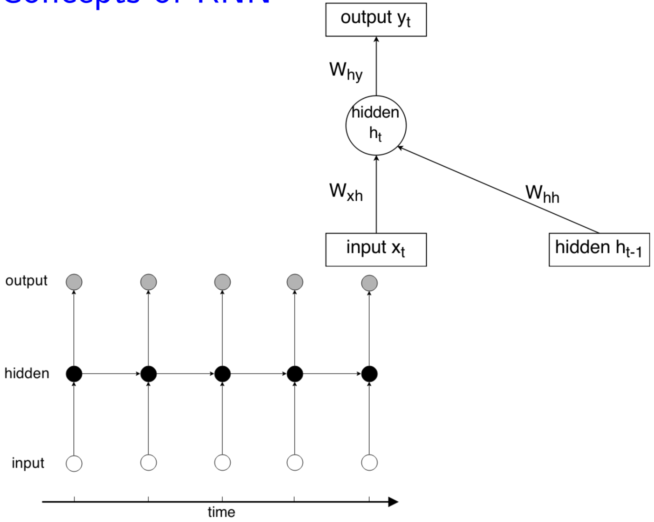

Long short term memory

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