Deep Neural Network for Speech Emotion Recognition

—A Study of Deep Learning—

Zhuowei Han

Institut für Signalverarbeitung
und Systemtheorie

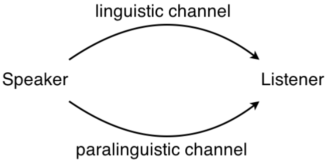
Universität Stuttgart

05.06.2014

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

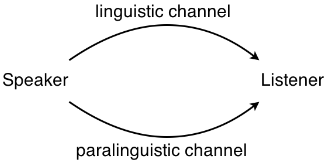
- Handwriting Digit Recognition
- Image Recognition

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

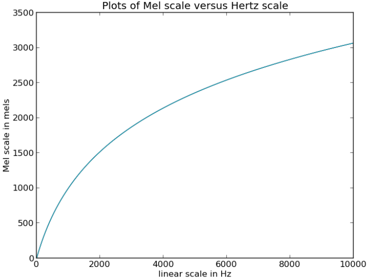
- Handwriting Digit Recognition
- Image Recognition

Table of Contents

Table of Contents

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



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

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

Emotion Recognition Approaches

Traditional Approaches

- pre-selected features
- supervised training
- low-level features not appropriate for claasification
- shallow structure of classifiers

Deep Learning Approaches

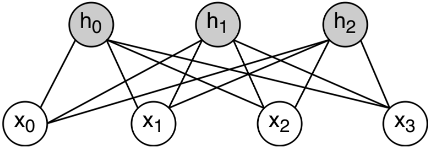
- learning representations from high-dim data
- extracting appropriate features without hand-crafting
- low-level features are used to build high-level features as network gets deeper
- frame-based classfication

Table of Contents

Character

- Generative model
- Undirected graphical model, good at modeling high-dimensioanl data (speech emotion)
- Trained in unsupervised way, only use unlabeled input sequence$\mathbf{x}$ for learning.
  - automatically extract useful features from data
  - Find hidden structure (distribution).
  - Learned features used for prediction or classification
- Potential to be extend to capture temporal information.

Structure



Energy Function: $E_{\boldsymbol{\theta}} = -\mathbf{x}^{\mathbf{T}}\mathbf{W}\mathbf{h} - \mathbf{b}^{\mathbf{T}}\mathbf{x} - \mathbf{c}^{\mathbf{T}}\mathbf{h}$

Joint Distribution: $P^{RBM}(\mathbf{x},\mathbf{h}) = \frac{1}{Z} e^{-E_{\boldsymbol{\theta}}(\mathbf{x},\mathbf{h})}$

Partition Function: $Z = \sum_{\mathbf{x},\mathbf{h}} e^{-E_{\boldsymbol{\theta}}(\mathbf{x},\mathbf{h})}$

Inference

$$P(h_j = 1 \mid \mathbf{x}) = sigmoid(\sum_i x_i W_{ij} + c_j)$$

$$P(x_i = 1 \mid \mathbf{h}) = sigmoid(\sum_j W_{ij} h_j + b_i)$$

Table of Contents

Computing net-activation

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

- Arbitrary non-linear mapping from $\underline{x}_k$ to $\hat{\underline{y}}_k$ 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)

Problems

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

Solutions

- Layerwise Pre-training

- Layerwise Pre-training

Table of Contents

Concepts of RNN

- modelling sequential data, emotion in speech .
- Same Structure as MLP but differs from feed-forward network, enabling nonlinear mapping.
- Feedback connection between previous hidden units and current hidden units, enabling memory past hidden state.
- Potentially to model arbitary dynamic system.
- Trained with **b**ack**p**ropagation **t**hrough **t**ime (BPTT)

Concepts of RNN

- modelling sequential data, emotion in speech .
- Same Structure as MLP but differs from feed-forward network, enabling nonlinear mapping.
- Feedback connection between previous hidden units and current hidden units, enabling memory past hidden state.
- Potentially to model arbitary dynamic system.
- Trained with **b**ack**p**ropagation **t**hrough **t**ime (BPTT)

Concepts of RNN

- modelling sequential data, emotion in speech .
- 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 **b**ack**p**ropagation **t**hrough **t**ime (BPTT)

Concepts of RNN

- modelling sequential data, emotion in speech .
- Same Structure as MLP but differs from feed-forward network, enabling nonlinear mapping.
- Feedback connection between previous hidden units and current hidden units, enabling memory past hidden state.
- Potentially to model arbitary dynamic system.
- Trained with **b**ack**p**ropagation **t**hrough **t**ime (BPTT)

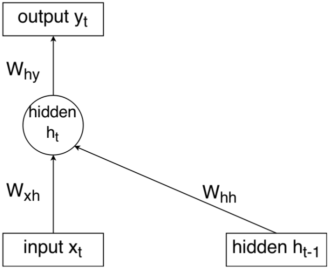
Concepts of RNN

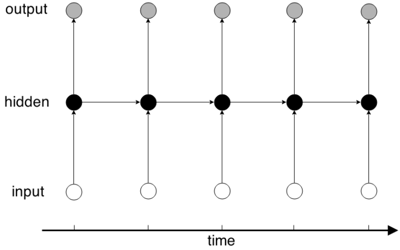
- modelling sequential data, emotion in speech .
- Same Structure as MLP but differs from feed-forward network, enabling nonlinear mapping.
- Feedback connection between previous hidden units and current hidden units, enabling memory past hidden state.
- Potentially to model arbitary dynamic system.
- Trained with **b**ack**p**ropagation **t**hrough **t**ime (BPTT)

Concepts of RNN

- modelling sequential data, emotion in speech .
- Same Structure as MLP but differs from feed-forward network, enabling nonlinear mapping.
- Feedback connection between previous hidden units and current hidden units, enabling memory past hidden state.
- Potentially to model arbitary dynamic system.
- Trained with **b**ack**p**ropagation **t**hrough **t**ime (BPTT)

Concepts of RNN





From RNN to LSTM

Problems with RNN

- gradient vanishing during backpropagation as time steps increases ($>$100)
- difficult to capture long-time dependency (which is required in emotion recognition)

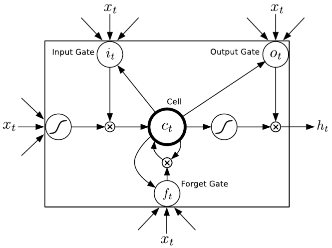
Solutions

-

Long short term memory

S. Hochreiter and J. Schmidhuber, Lovol. 9, pp. 1735-1780, 1997.

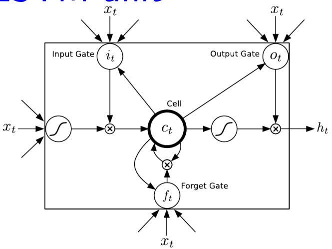
LSTM unit



$$
\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \\
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \\
c_t &= f_t c_{t-1} + i_t \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b \\
o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \\
h_t &= o_t \tanh(c_t)
\end{aligned}
$$

Long short term memory

LSTM unit



$$
\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \\
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \\
c_t &= f_t c_{t-1} + i_t \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b \\
o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \\
h_t &= o_t \tanh(c_t)
\end{aligned}
$$

Features in LSTM

- gates are trained to learn when it shoud be open/closed.
- Constant Error Carousel
- preserve long-time dependency by maintaining gradient over time.

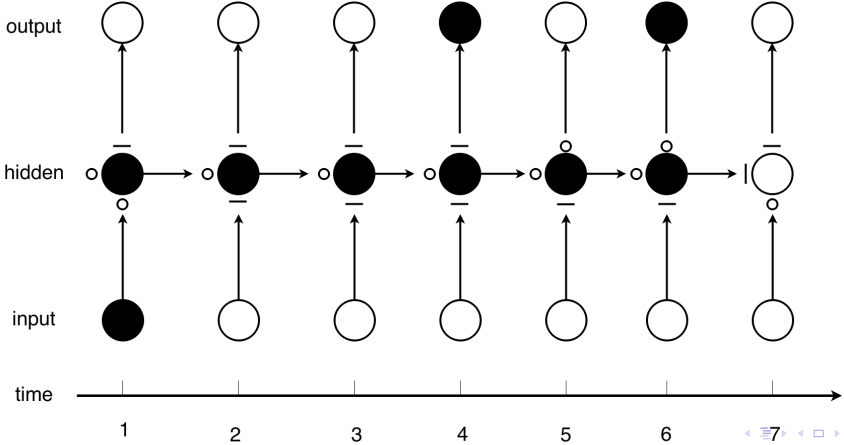


Table of Contents

Table of Contents