Deep Neural Network for Speech Emotion Recognition

—A Study of Deep Learning—

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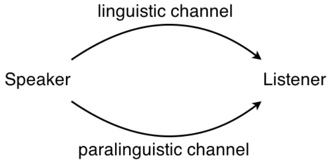
05.06.2014

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

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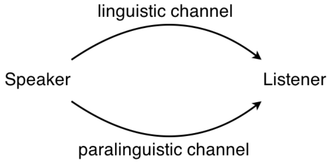

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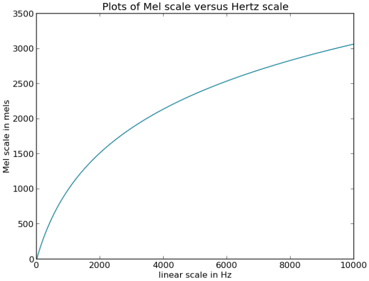
Mel Frequency Cepstral Features

- short-term power spectrum
- mel-scale approximate human perception
- widely-used in speech recognition tasks
- Transformation between Mel and Hertz scale



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

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

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

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Restricted BM

- undirected graphical probablistic model based on PoE, capable in modeling high-dimensioanl data (speech emotion)
- speicifies a joint distribution over input and hidden variables, can either generating data, or with bayesian rule to form conditional distribution.

Desired: $P(x, h)$

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Computing net-activation

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

- 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)

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

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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)

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

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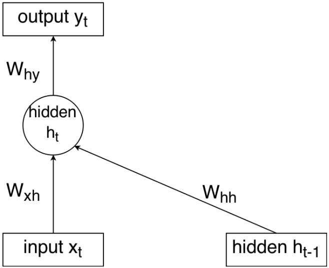
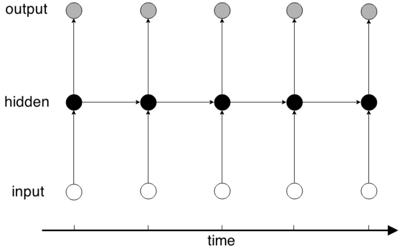




From RNN to LSTM

Problems with RNN

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

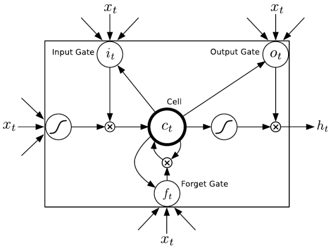
Solutions

-

Long short term memory

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

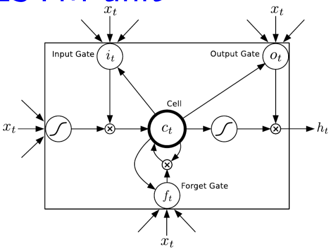
LSTM unit



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

Long short term memory

LSTM unit



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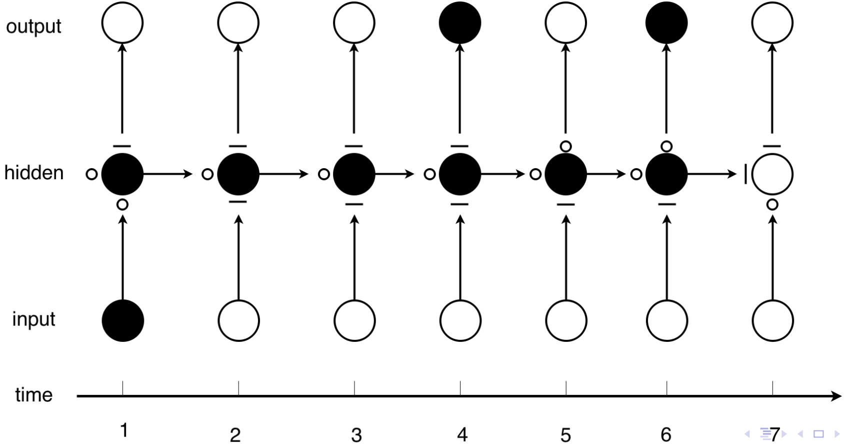
Features in LSTM

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



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