Deep Network for Speech Emotion Recognition

—A Study of Deep Learning—

Zhuowei Han

Institut für Signalverarbeitung
und Systemtheorie

Universität Stuttgart

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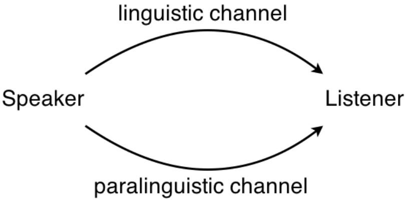
Speech Emotion Recognition

- 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 Learning

- Deep architecture for extracting complex structure and building internal representations from input
- New research area of machine learning (from shallow to deep structure)
- Widely applied in vision/audition processing, e.g. handwriting recognition (Graves, Alex, et al. 2009), traffic sign classification (Schmidhuber, et al. 2011), text translation (Google, 2014)

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- Mel Frequency Cepstral Features
- Emotion Recognition Approaches

Conditional Restricted Boltzmann Machine
- Restricted Boltzmann Machine
- CRBM

Conclusion and Outlook

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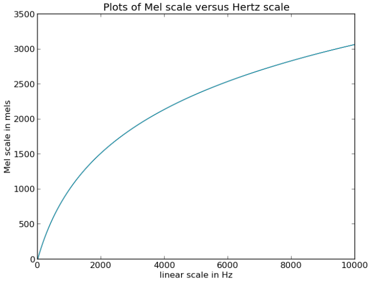
Mel Frequency Cepstral Features

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



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

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 classification

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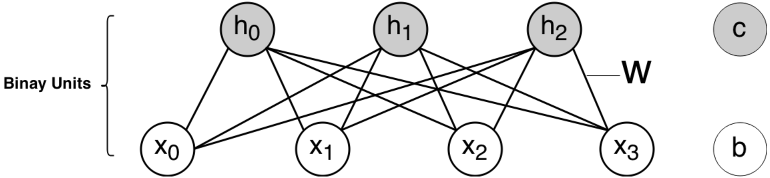
Concepts

- Generative graphical model, capture data distrbution $P(\mathbf{x}|\boldsymbol{\theta})$
- 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
- Successfully applied in motion capture (Graham W. Taylor, Geoffrey E. Hinton, 2006)
- Potential to be extend to capture temporal information

Structure



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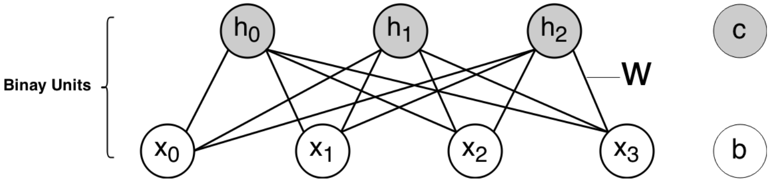

Energy Function: $E_{\boldsymbol{\theta}} = -\mathbf{x}^{\mathbf{T}}\mathbf{W}\mathbf{h} - \mathbf{b}^{\mathbf{T}}\mathbf{x} - \mathbf{c}^{\mathbf{T}}\mathbf{h}$

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

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

Free Energy: $\mathcal{F}(\mathbf{x}) = -\log \sum_{h} e^{-E(\mathbf{x},\mathbf{h})}$

Inference

$$P(\mathbf{x}) = \sum_{\mathbf{h}} P(\mathbf{x}, \mathbf{h})$$

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

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

Conditional RBM

- Consider visible units from previous time step as additional bias for current visible and hidden layer
- A and B are weight parameter of visible (history) - visible and visible (history) - hidden connections
- Visible layer is linear units with independent Gaussian noise to model real-valued data, e.g. spectral features

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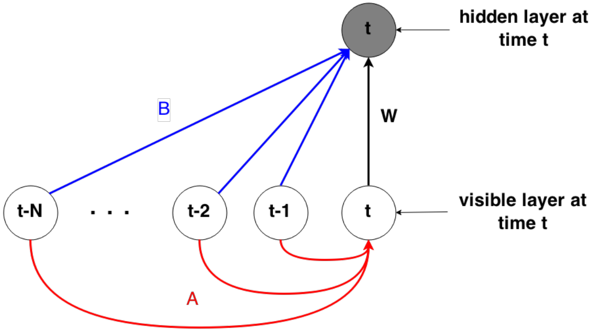
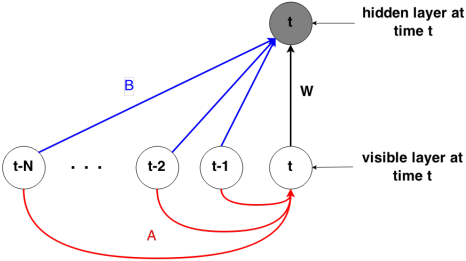


Conditional RBM



$$\text{Energy Function: } E_{\boldsymbol{\theta}}^{CRBM}(\mathbf{x}, \mathbf{h}) = \left\| \frac{\mathbf{x} - \tilde{\mathbf{b}}}{2} \right\|^2 - \tilde{\mathbf{c}}^T \mathbf{h} - \mathbf{x}^T \mathbf{W} \mathbf{h}$$

$$\tilde{\mathbf{b}} = \mathbf{b} + \mathbf{A} \cdot \mathbf{x}_{<t}$$

$$\tilde{\mathbf{c}} = \mathbf{c} + \mathbf{B} \cdot \mathbf{x}_{<t}$$

$$\boldsymbol{\theta} = \{\mathbf{W}, \mathbf{A}, \mathbf{B}, \mathbf{b}, \mathbf{c}\}$$

$$\text{Free Energy: } \mathcal{F}(\mathbf{x}) = \left\| \mathbf{x} - \tilde{\mathbf{b}} \right\|^2 - \log(1 + e^{\tilde{\mathbf{c}} + \mathbf{x} \cdot \mathbf{W}})$$

Training of Energy-based Model

Maximum Likelihood Estimation $P(\mathbf{x}|\boldsymbol{\theta})$

Note that KL is non-negative

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Kullback-Leibler Divergence:

$$
\begin{aligned}
Q(\mathbf{x})\|P(\mathbf{x}|\boldsymbol{\theta}) &= \int_{-\infty}^{\infty} Q(\mathbf{x}) \cdot \log \frac{Q(\mathbf{x})}{P(\mathbf{x}|\boldsymbol{\theta})} \mathrm{d}\mathbf{x} \\
&= \int_{-\infty}^{\infty} Q(\mathbf{x}) \cdot \log Q(\mathbf{x}) \mathrm{d}\mathbf{x} - \int_{-\infty}^{\infty} Q(\mathbf{x}) \cdot \log P(\mathbf{x}|\boldsymbol{\theta}) \mathrm{d}\mathbf{x} \\
&= \langle \log Q(\mathbf{x}) \rangle_{Q(\mathbf{x})} - \langle \log P(\mathbf{x}|\boldsymbol{\theta}) \rangle_{Q(\mathbf{x})}
\end{aligned}
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$Q(\mathbf{x})$, true data distribution
$P(\mathbf{x}|\boldsymbol{\theta})$, model distribution
$\langle \cdot \rangle_{Q(\mathbf{x})}$, expectation w.r.t. $Q(\mathbf{x})$
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$\tilde{\mathbf{x}}$, all possible vectors in the data space, generated by model.

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objective function by averaging log-likelihood over data:

$$-\left\langle \frac{\partial \log P(\mathbf{x}|\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right\rangle_{\mathbf{x}} = \left\langle \frac{\partial \mathcal{F}(\mathbf{x})}{\partial \boldsymbol{\theta}} \right\rangle_{\mathbf{x}} - \left\langle \frac{\partial \mathcal{F}(\tilde{\mathbf{x}})}{\partial \boldsymbol{\theta}} \right\rangle_{\tilde{\mathbf{x}}}$$

Gibbs sampling

$$\mathbf{x}^{(1)} \sim P(\mathbf{x})$$

$$\mathbf{h}^{(1)} \sim P(\mathbf{h}|\mathbf{x}^{(1)})$$

$$\mathbf{x}^{(2)} \sim P(\mathbf{x}|\mathbf{h}^{(1)})$$

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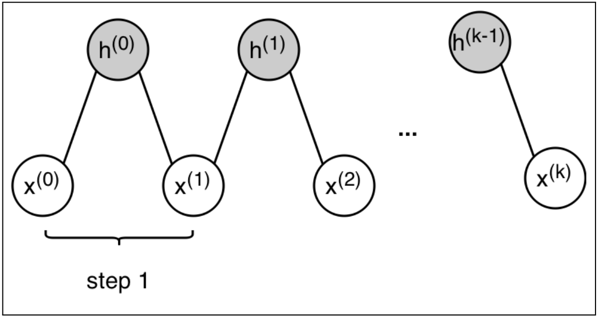

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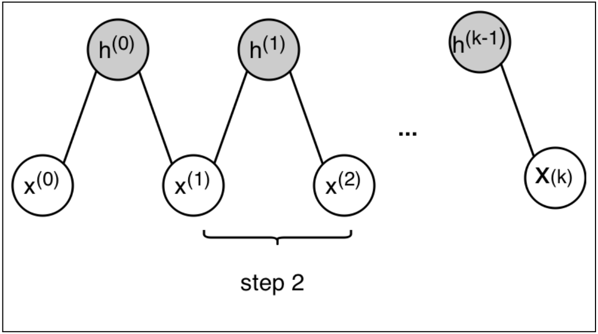

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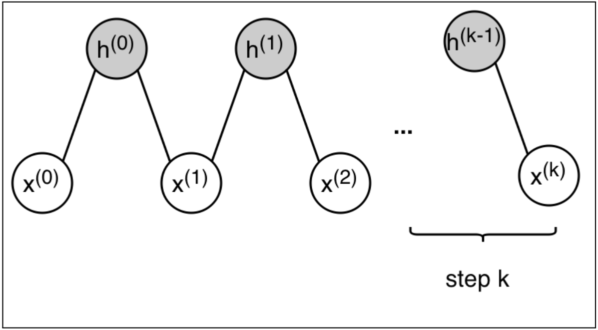

Contrastive Divergence

- k=0, $P_0(\mathbf{x})$ is true data distribution, independent of parameter $\boldsymbol{\theta}$
- Performing k-Gibbs steps to generate $P_k(\mathbf{x}|\boldsymbol{\theta})$, with $k \to \infty$ the Markov chain converges to stationary distribution:

$$P_\infty(\mathbf{x}|\boldsymbol{\theta}) \to P(\tilde{\mathbf{x}}|\boldsymbol{\theta})$$

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Rewrite objective function:

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Contrastive Divergence: Perform CD-1

$$
\begin{aligned}
&-\frac{\partial}{\partial\boldsymbol{\theta}}(P_0 \| P_\infty^{\boldsymbol{\theta}} - P_1^{\boldsymbol{\theta}} \| P_\infty^{\boldsymbol{\theta}}) \\
&= \left\langle \frac{\partial\mathcal{F}(\mathbf{x})}{\partial\boldsymbol{\theta}} \right\rangle_{P_0} - \left\langle \frac{\partial\mathcal{F}(\mathbf{x})}{\partial\boldsymbol{\theta}} \right\rangle_{P_1^{\boldsymbol{\theta}}} + \frac{\partial P_1^{\boldsymbol{\theta}}}{\partial\boldsymbol{\theta}} \frac{\partial(P_1^{\boldsymbol{\theta}} | P_\infty^{\boldsymbol{\theta}})}{\partial P_1^{\boldsymbol{\theta}}}
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\end{aligned}
$$

Parameter Update

$$
\Delta \boldsymbol{\theta} \sim \left\langle \frac{\partial \mathcal{F}(\mathbf{x})}{\partial \boldsymbol{\theta}} \right\rangle_{P_0} - \left\langle \frac{\partial \mathcal{F}(\mathbf{x})}{\partial \boldsymbol{\theta}} \right\rangle_{P_1^{\boldsymbol{\theta}}}
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Conclusion

- Model with long-term dependencies shall be used for speech emotion
- CRBM is appropriate for short-term modelling, but not for long-term variation
- LSTM is good at modelling long time dependency
- Frame-based classification can also reach good result
  - CRBM-LSTM 71.98%
  - LSTM 81.59%
  - LSTM with rectifier layers 83.43%

Outlook

- Stacking CRBM to form deeper structure
- Train CRBM with more/larger database
- Second order optimization to speed up learning process
- Bi-directional LSTM, capturing future dependencies

Thank You!