Deep Network for Speech Emotion Recognition

Master Thesis

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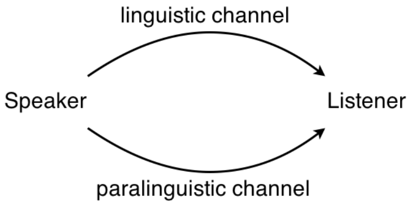
Speech Emotion Recognition

- More natural human-machine interaction requires paralinguistic information such as age, gender, emotion.
- Emotion is high-dimensional complex data with non-linear time-variant hidden features
- Traditional feature learning is labor expensive



Deep Learning

- New research area of machine learning
- Deep architecture for building high-level representations via unsupervised feature learning
- Learning both temporal and non-temporal features
- Application 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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Framework of Emotion Recognition

- Extract spectrum features: Mel Frequency Cepstral Coefficients
- Aggregate MFCCs to build high-level representations via unsupervised learning
- Classification based on high-level features via supervised learning

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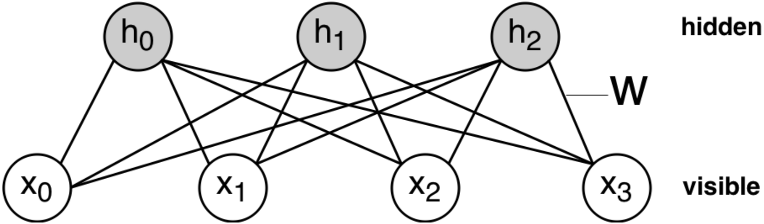
Conditional Restricted Boltzmann Machine

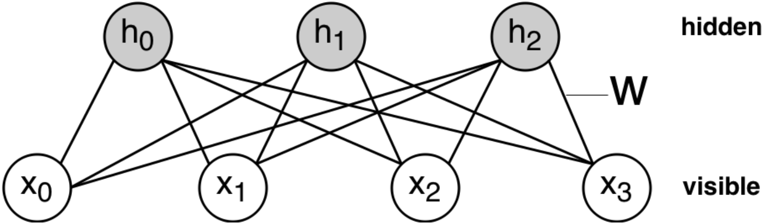
- Energy-based undirected graphical model
- Contains hidden variables (hidden units), increases the modeling capacity.
- Unsupervised feature learning
  - build high-level features from low-level features
  - learned features used for prediction or classification
- Successfully applied in motion capture (Graham W. Taylor, Geoffrey E. Hinton, 2006)

Structure



visible/input layer	$\mathbf{x} \in \{0, 1\}$
hidden layer	$\mathbf{h} \in \{0, 1\}$
weight	$\mathbf{W}$
visible bias	$\mathbf{b}$
hidden bias	$\mathbf{c}$
parameter set	$\boldsymbol{\theta} = \{\mathbf{W}, \mathbf{b}, \mathbf{c}\}$

Structure



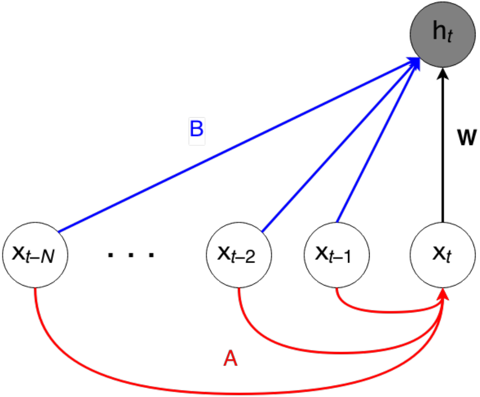
Energy Function: $E_{\boldsymbol{\theta}}(\mathbf{x},\mathbf{h}) = -\mathbf{x}^{\mathbf{T}}\mathbf{W}\mathbf{h} - \mathbf{b}^{\mathbf{T}}\mathbf{x} - \mathbf{c}^{\mathbf{T}}\mathbf{h}$

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

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

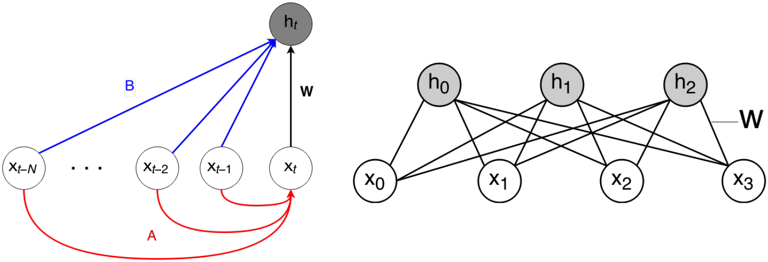
Free Energy: $\mathcal{F}(\mathbf{x}) = -\log \sum_{h} e^{-E(\mathbf{x},\mathbf{h})}$

Conditional RBM



- Consider visible units from previous time step as additional bias for current visible and hidden layer
- Visible layer consists of linear units with independent Gaussian noise to model real-valued data, e.g. spectral features

Conditional RBM



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

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

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

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

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

Inference

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

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

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

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

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

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

Training of Energy-based Model

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

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

Kullback-Leibler Divergence:

$$\begin{aligned} Q(\mathbf{x}) \| P^{\boldsymbol{\theta}}(\mathbf{x}) &= \int_{-\infty}^{\infty} Q(\mathbf{x}) \cdot \log \frac{Q(\mathbf{x})}{P^{\boldsymbol{\theta}}(\mathbf{x})} \mathrm{d}\mathbf{x} \\ &= \int_{-\infty}^{\infty} Q(\mathbf{x}) \cdot \log Q(\mathbf{x}) \mathrm{d}\mathbf{x} - \int_{-\infty}^{\infty} Q(\mathbf{x}) \cdot \log P^{\boldsymbol{\theta}}(\mathbf{x}) \mathrm{d}\mathbf{x} \\ &= \langle \log Q(\mathbf{x}) \rangle_{Q(\mathbf{x})} - \Big\langle \log P^{\boldsymbol{\theta}}(\mathbf{x}) \Big\rangle_{Q(\mathbf{x})} \end{aligned}$$

$Q(\mathbf{x})$, true data distribution

$P^{\boldsymbol{\theta}}(\mathbf{x})$, parameterized distribution, to be estimated

$\langle \cdot \rangle_{Q(\mathbf{x})}$, expectation w.r.t. $Q(\mathbf{x})$

Training of Energy-based Model

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

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&= \int_{-\infty}^{\infty} Q(\mathbf{x}) \cdot \log Q(\mathbf{x}) \mathrm{d}\mathbf{x} - \int_{-\infty}^{\infty} Q(\mathbf{x}) \cdot \log P^{\boldsymbol{\theta}}(\mathbf{x}) \mathrm{d}\mathbf{x} \\
&= \langle \log Q(\mathbf{x}) \rangle_{Q(\mathbf{x})} - \left\langle \log P^{\boldsymbol{\theta}}(\mathbf{x}) \right\rangle_{Q(\mathbf{x})}
\end{aligned}
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Training of Energy-based Model

$$-\log P^{\boldsymbol{\theta}}(\mathbf{x}) = \mathcal{F}(\mathbf{x}) + \log \sum_{\mathbf{x}} \sum_{\mathbf{h}} e^{-E_{\boldsymbol{\theta}}(\mathbf{x},\mathbf{h})}$$

$$-\frac{\partial \log P^{\boldsymbol{\theta}}(\mathbf{x})}{\partial \boldsymbol{\theta}} = \frac{\partial \mathcal{F}(\mathbf{x})}{\partial \boldsymbol{\theta}} - \sum_{\tilde{\mathbf{x}}} P(\tilde{\mathbf{x}}) \frac{\partial \mathcal{F}(\tilde{\mathbf{x}})}{\partial \boldsymbol{\theta}}$$

$\mathbf{x}$, input (visible) data space
$\tilde{\mathbf{x}}$, all possible vectors in the data space, generated by model.

Training of Energy-based Model

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objective function by averaging log-likelihood over data:

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

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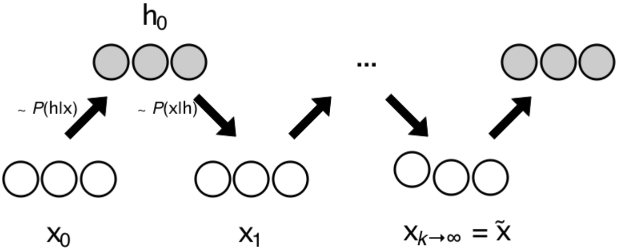
Contrastive Divergence (Hinton)

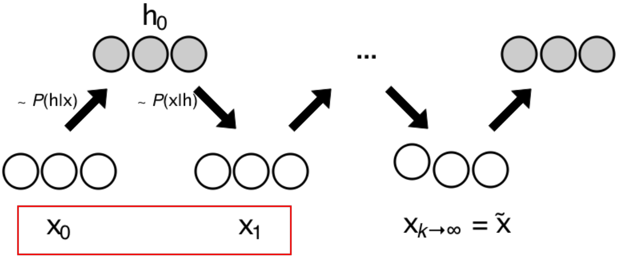
- Obtain $P(\tilde{\mathbf{x}})$ by Gibbs sampling
- k=0, $P_0(\mathbf{x})(= Q(\mathbf{x}))$ is true data distribution, independent of parameter $\boldsymbol{\theta}$
- $P^{\boldsymbol{\theta}}_{\infty}(\mathbf{x}) \to P(\tilde{\mathbf{x}})$



Contrastive Divergence (Hinton)

- In practise perform 1-Gibbs step will work well:

$$-\left\langle \frac{\partial \log P^{\boldsymbol{\theta}}(\mathbf{x})}{\partial \boldsymbol{\theta}} \right\rangle_{P_0(\mathbf{x})} = \left\langle \frac{\partial \mathcal{F}(\mathbf{x})}{\partial \boldsymbol{\theta}} \right\rangle_{P_0(\mathbf{x})} - \left\langle \frac{\partial \mathcal{F}(\mathbf{x})}{\partial \boldsymbol{\theta}} \right\rangle_{P_1^{\boldsymbol{\theta}}(\mathbf{x})}$$



Contrastive Divergence (Hinton)

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

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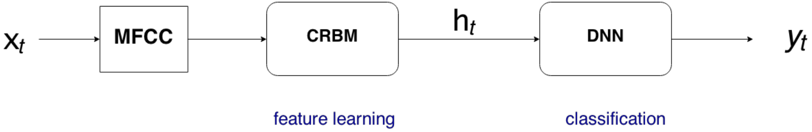
DNN for Classification

- Using high-level features to perform classification
- DNN Structure
  - Feedforward network
  - Recurrent network



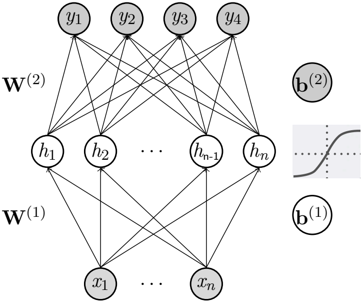
Feedforward Structure

Hidden layer pre-activation:

$$\mathbf{a}(\mathbf{x}) = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}$$

Hidden layer activation:

$$\mathbf{h} = f(\mathbf{a})$$



Output layer activation of single hidden layer:

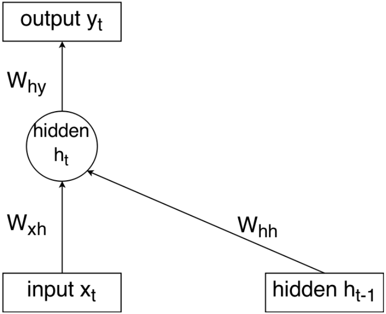
$$\hat{y}(\mathbf{x}) = o(\mathbf{W}^{(2)}\mathbf{h}^{(1)} + \mathbf{b}^{(2)})$$

Output layer activation of N hidden layers:

$$\hat{y}(\mathbf{x}) = o(\mathbf{W}^{(N+1)}\mathbf{h}^{(N)} + \mathbf{b}^{(N+1)})$$

Recurrent Structure

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



Empirical Risk Minimization

- Objective

$$\arg\min_{\boldsymbol{\theta}} \frac{1}{M} \sum_{m} l(\hat{y}(\mathbf{x}^{(m)};\boldsymbol{\theta}), y^{(m)}) + \lambda \Omega(\boldsymbol{\theta})$$

- Loss function $l(\hat{y}(\mathbf{x}^{(m)};\boldsymbol{\theta}), y^{(m)})$, $\boldsymbol{\theta} = \{\mathbf{W}, \mathbf{b}\}$
- Regularizer $\lambda \Omega(\boldsymbol{\theta})$, L1 & L2 regularization

Optimization

- Stochastic gradient descent
- Layerwise pre-training & Backpropagation (BP)

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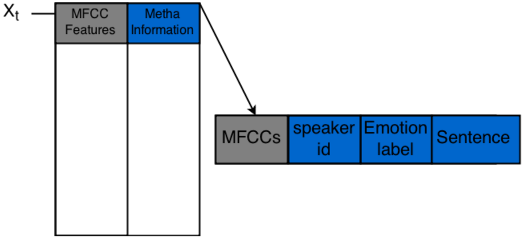
Experiment Setup

EmoDB Database

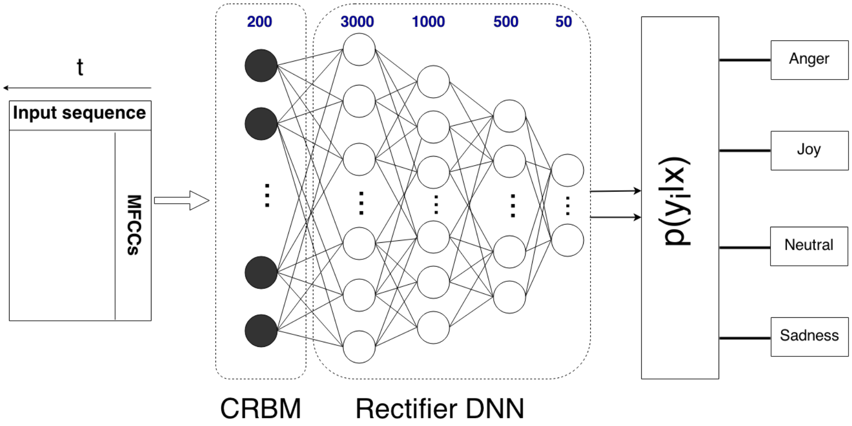
	Joy	Neutral	Sadness	Anger	Total
No. of sentences	71	79	62	127	339
Percent (%)	21	23.2	18.3	37.5	100

Data Structure



Experiment Result

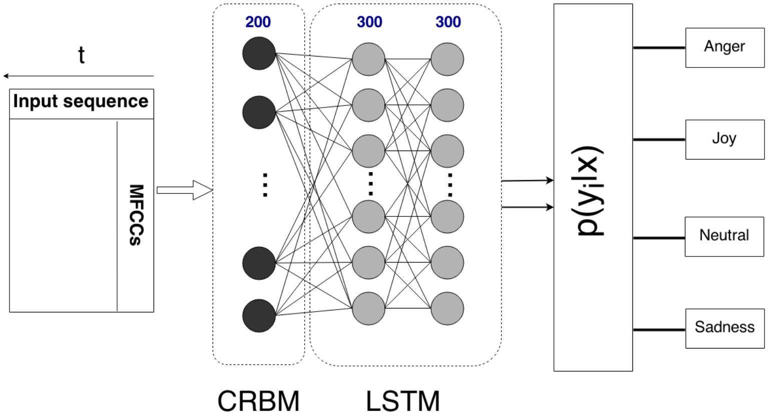
- CRBM-DNN



Confusion matrix of CRBM-DNN result.

		Classfied			
		Joy	Neutral	Sadness	Anger
	Joy	57.7%	1.4%	0.0%	40.8%
True	Neutral	17.7%	54.4%	25.3%	2.5%
	Sadness	1.6%	27.9%	70.5%	0.0%
	Anger	39.4%	1.6%	0.0%	59.1%
		recognition rate:59.76%			

- CRBM-LSTM


t
Input sequence
MFCCs
200
300
300
CRBM
LSTM
p(y_i|x)
Anger
Joy
Neutral
Sadness

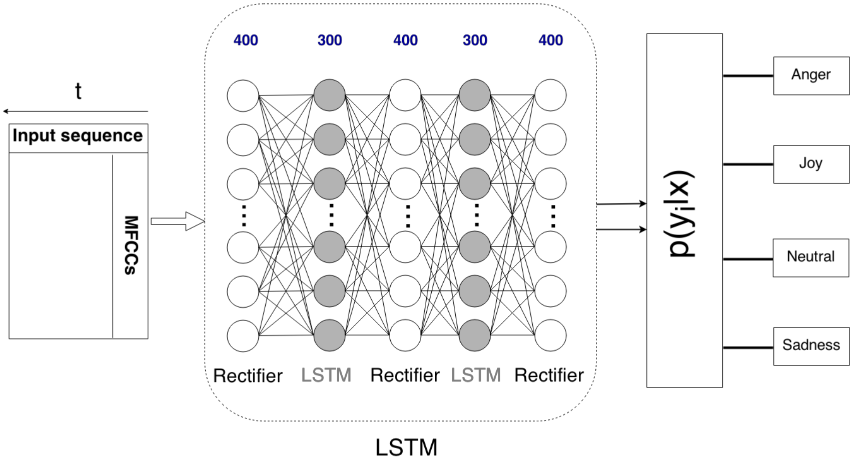
Experiment Result

Confusion matrix of CRBM-LSTM result.

		Classfied			
		Joy	Neutral	Sadness	Anger
	Joy	11.3%	9.9%	2.8%	76.1%
True	Neutral	0.0%	72.2%	17.7%	10.1%
	Sadness	0.0%	4.8%	88.7%	6.5%
	Anger	0.8%	1.6%	0.0%	97.6%
		recognition rate: 71.98%			

Experiment Result

- LSTM with rectifier units



Experiment Result

Confusion matrix of LSTM-Rectifier result.

		Classfied			
		Joy	Neutral	Sadness	Anger
	Joy	57.7%	7.0%	0.0%	35.2%
True	Neutral	6.3%	86.1%	6.3%	1.3%
	Sadness	0.0%	6.6%	93.4%	0.0%
	Anger	8.7%	0.0%	0.0%	91.3%
recognition rate: 83.43%					

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Conclusion

- Capturing long-term dependencies is necessary for speech emotion recognition
- CRBM-DNN is inappropriate for speech emotion recognition (ER: 40.24%)
- CRBM can capture non-temporal and temporal dependencies, but only short term

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Model	Temporal Dependency	Memory	Generaltive
DNN	-	-	-
RBM	-	-	✓
CRBM	✓	2-5	✓
AE	-	-	-
RNN	✓	1-100	-
LSTM	✓	1-1000	-

Conclusion

- Capturing long-term dependencies is necessary for speech emotion recognition
- CRBM-DNN is inappropriate for speech emotion recognition (ER: 40.24%)
- CRBM can capture non-temporal and temporal dependencies, but only short term
- Frame-based classification can also reach good result
  - CRBM-LSTM 71.98%
  - LSTM with rectifier layers 83.43%
  - Sentence-based model SVM 84.26% (Tobias Gruber 2014)

Outlook

- Stacking CRBM to form deep belief network
- Second order optimization to speed up learning process, e.g. Newton methods
- Bi-directional LSTM

Thank You!

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