

Deep Network for Speech Emotion Recognition

—A Study of Deep Learning—



Zhuowei Han

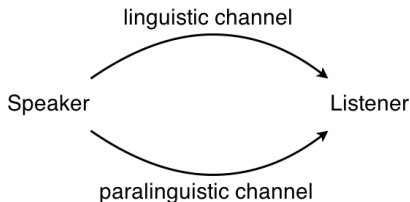
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Speech Emotion Recognition

- More natural human-machine interaction requires paralinguistic information such as age, gender, emotion.
- Emotion data are high-dimensional complex data with non-linear temporal hidden features
- GMM is not sufficient enough to modelling speech emotion



Deep Learning

- New research area of machine learning (from shallow to deep structure)
- Deep architecture for extracting complex structure and building internal representations via unsupervised learning
- 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)

Foundations

Conditional Restricted Boltzmann Machine

Restricted Boltzmann Machine

CRBM

Deep Neural Network

Function and Training

Problems and Solutions

Long Short Term Memory

Experiments

Conclusion and Outlook

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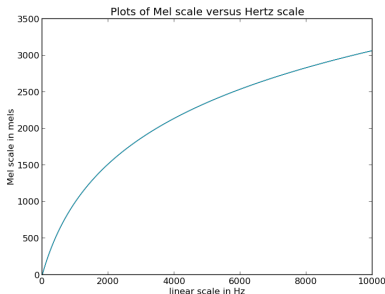
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Mel Frequency Cepstral Coefficients

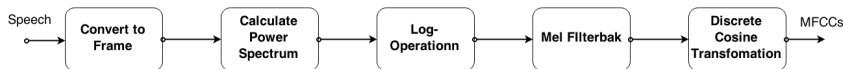
- most commonly used features in speech emotion analysis
- short-term power spectrum based on frame
- mel-scale approximate human perception

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



Steps to MFCCs

1. Convert speech signal with overlapped window to frames ($20ms$ frame length, $10ms$ shifting).
2. Calculate power spectrum for each frame with DFT and take the logarithm value.
3. Apply Mel filterbank to the power spectrum, sum the power in each filter.
4. Decorrelation by applying Discrete Cosine Transform (DCT) to the logarithm of the filter powers.
5. Keep coefficients 1 – 20 of DCT and discard the rest.



Framework of Emotion Recognition

- Pre-processing of emotion data to extract MFCC features
- Model data distribution based on MFCCs via unsupervised learning
- Classification with supervised learning



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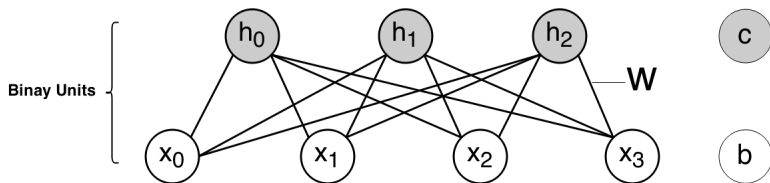
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- Generative energy-based graphical model, capture data distribution $P(\mathbf{x}|\boldsymbol{\theta})$
- Trained in unsupervised way, only use unlabeled input sequence \mathbf{x} for learning.
 - automatically extract useful features from data
 - find hidden structure (distribution).
 - learned features used for prediction or classification
- Successfully applied in motion capture (Graham W. Taylor, Geoffrey E. Hinton, 2006)
- non-temporal, but is potential to be extended to capture temporal information

Structure



visible/input layer

$$\mathbf{x} \in \{0, 1\}$$

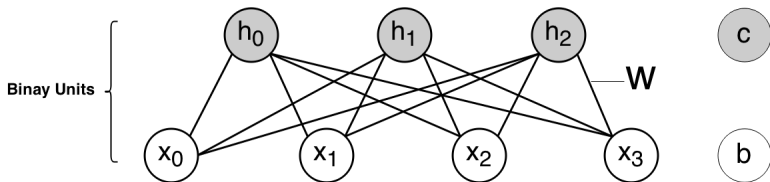
hidden layer

$$\mathbf{h} \in \{0, 1\}$$

parameter set

$$\theta = \{\mathbf{W}, \mathbf{b}, \mathbf{c}\}$$

Structure



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

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

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

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

Inference

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

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

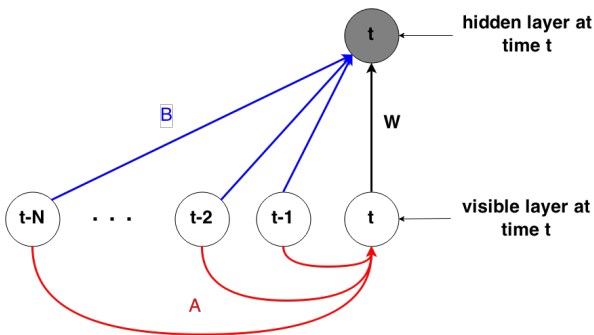
$$P(\mathbf{x}|\mathbf{h}) = \frac{P(\mathbf{x}, \mathbf{h})}{P(\mathbf{h})}$$

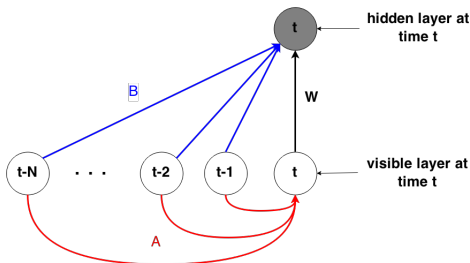
$$P(h_j = 1 \mid \mathbf{x}) = \text{sigmoid}(\sum_i x_i W_{ij} + c_j)$$

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

- 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 consists of linear units with independent Gaussian noise to model real-valued data, e.g. spectral features

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

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

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

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

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

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

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Kullback-Leibler Divergence:

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

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

$P(\mathbf{x}|\boldsymbol{\theta})$, model distribution

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

Note that KL is non-negative

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\mathbf{x} , input (visible) data space

$\tilde{\mathbf{x}}$, 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

$$\mathbf{x}^{(0)} \sim P(\mathbf{x})$$

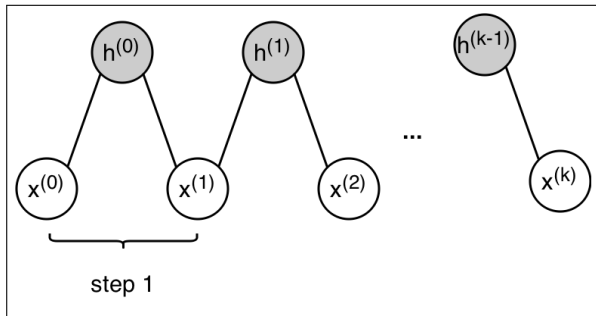
$$\mathbf{h}^{(0)} \sim P(\mathbf{h}|\mathbf{x}^{(0)})$$

$$\mathbf{x}^{(1)} \sim P(\mathbf{x}|\mathbf{h}^{(0)})$$

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⋮

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



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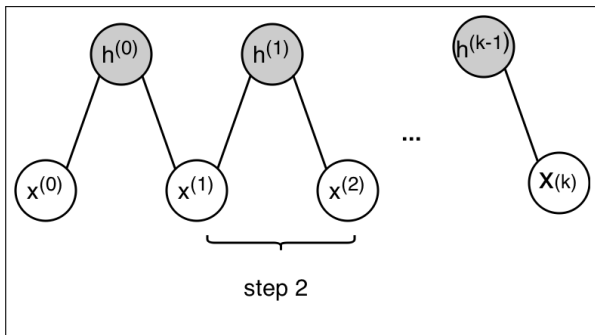
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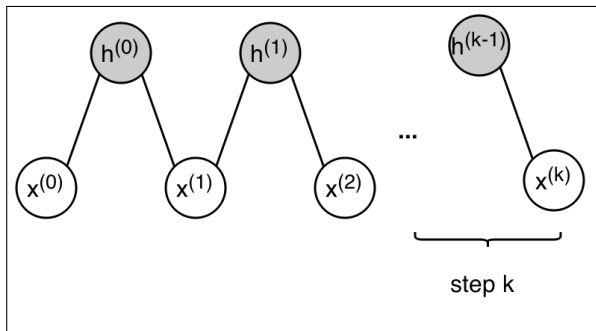
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- $k=0$, $P_0(\mathbf{x})$ is true data distribution, independent of parameter θ
- Performing k -Gibbs steps to generate $P_k(\mathbf{x}|\theta)$, with $k \rightarrow \infty$ the Markov chain converges to stationary distribution:

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

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Rewrite objective function:

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Contrastive Divergence (Hinton):

Perform CD-1

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

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Parameter Update

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

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Hidden layer pre-activation:

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

$$a_j(\mathbf{x}) = \sum_i w_{ji}^{(1)} x_i + b_j^{(1)}$$

Hidden layer activation:

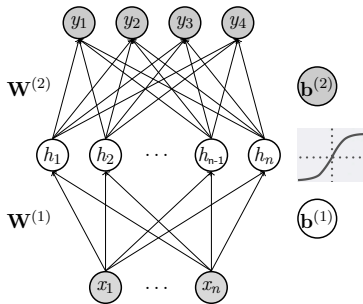
$$\mathbf{h} = f(\mathbf{a})$$

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:

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



Empirical Risk Minimization

- Objective

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

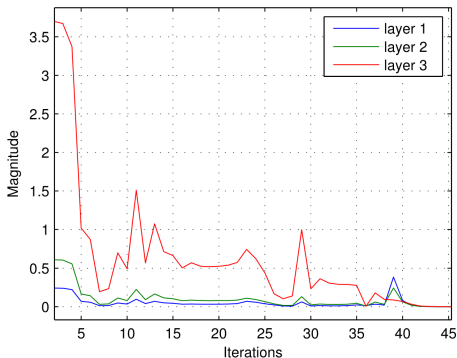
- loss function $l(\hat{y}(\mathbf{x}^{(m)}; \theta), y^{(m)})$, $\theta = \{\mathbf{W}, \mathbf{b}\}$
for sigmoid activation $l(\theta) = \sum_m \frac{1}{2} \|y^{(m)} - \hat{y}^{(m)}\|^2$
- regularizer $\lambda \Omega(\theta)$

Optimization

- Gradient calculation with Backpropagation (BP)
- Stochastic/Mini-batch gradient descent

Vanishing Gradient in BP

- Training time increases as network gets deeper
- Gradient shrink exponentially and training end up local minima
- Caused by random initialization of network parameters



Vanishing Gradient in BP

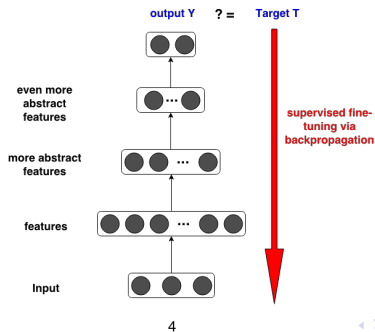
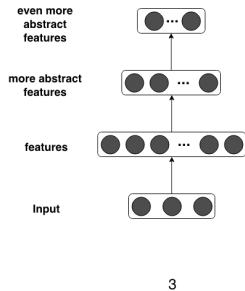
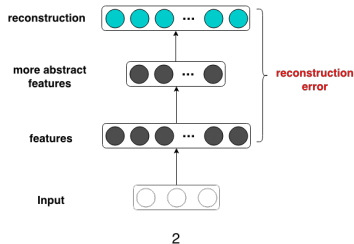
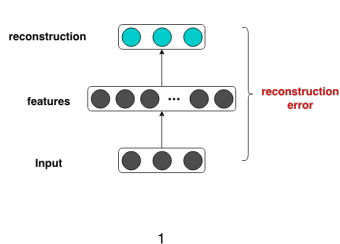
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Unsupervised layerwise pre-training

- Pretrain the deep network layer by layer in unsupervised way to build a stacked auto-encoder
- Each layer is trained as a single hidden layer auto-encoder by minimizing average reconstruction error:

$$\min l_{AE} = \sum_m \frac{1}{2} \left\| \mathbf{x}^{(m)} - \hat{\mathbf{x}}^{(m)} \right\|^2$$

- Fine-tuning the entire deep network with supervised training



Overfitting

- Huge amount of parameters in deep network
- Not enough data for training
- Poor generalization

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Regularization

- Add weight penalization $\lambda \|\mathbf{w}\|_p$ to loss function

$$\arg \min_{\theta} \frac{1}{M} \sum_m l(\hat{y}(\mathbf{x}^{(m)}; \theta), y^{(m)}) + \lambda \|\mathbf{w}\|_p$$

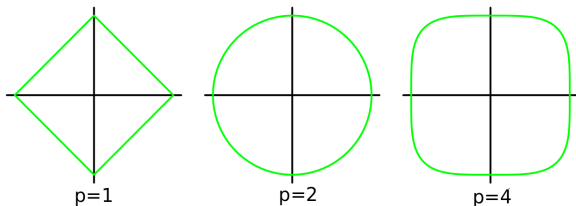
- In convex optimization:

$$\arg \min_{\theta} \frac{1}{M} \sum_m l(\hat{y}(\mathbf{x}^{(m)}; \theta), y^{(m)}), s.t. \|\mathbf{w}\|_p \leq C$$

P-Norm

$$\|\mathbf{w}\|_p := \left(\sum_{i=1}^n |w_i|^p \right)^{1/p} = \sqrt[p]{|w_1|^p + \dots + |w_n|^p}$$

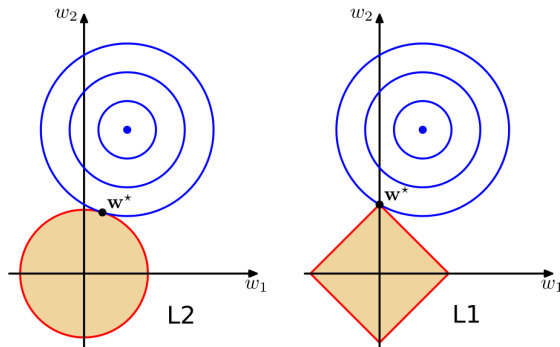
Widely used: L1- and L2-regularization ($p = 1$ and $p = 2$)



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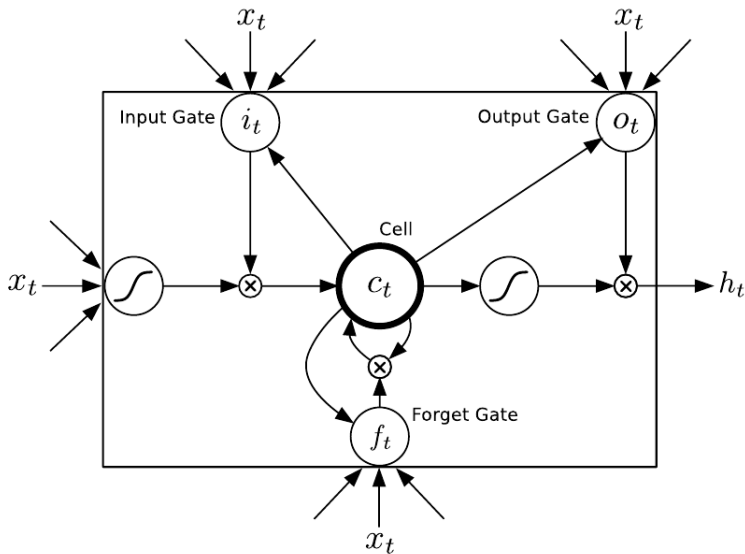
- gradient vanishing during backpropagation as time steps increases (>100)
- difficult to capture long-time dependency (which is required in emotion recognition)

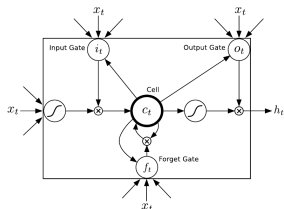
Problems with RNN

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- difficult to capture long-time dependency (which is required in emotion recognition)

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

Long short term memory





$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i)$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f)$$

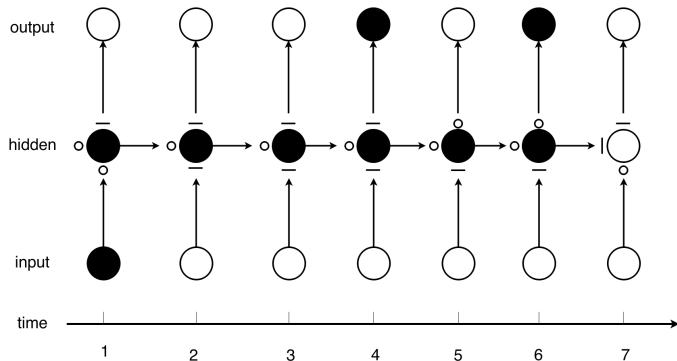
$$c_t = f_t c_{t-1} + i_t \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o)$$

$$h_t = o_t \tanh(c_t)$$

Features in LSTM

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



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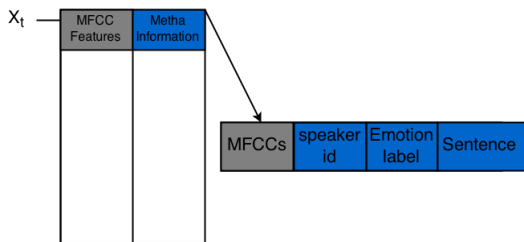
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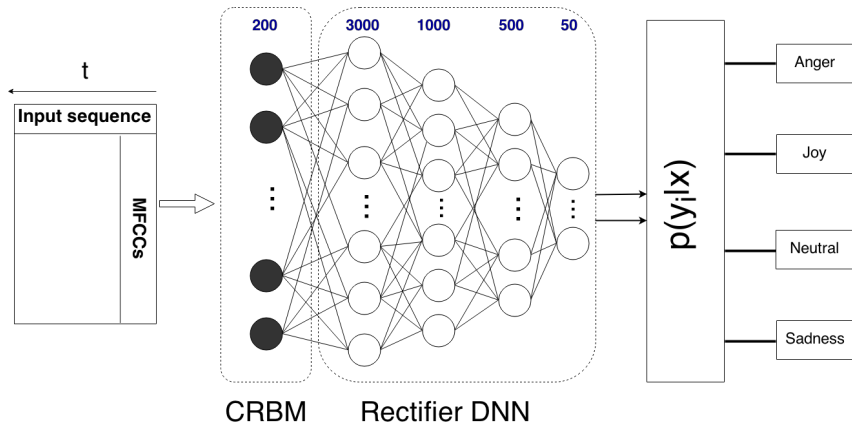
EmoDB Database

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

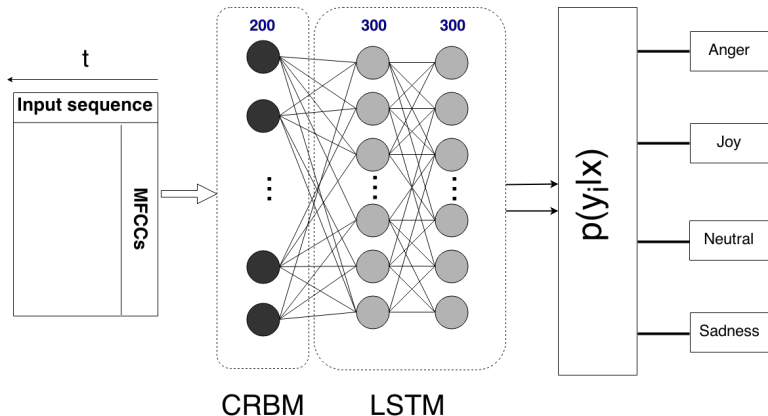
Data Structure



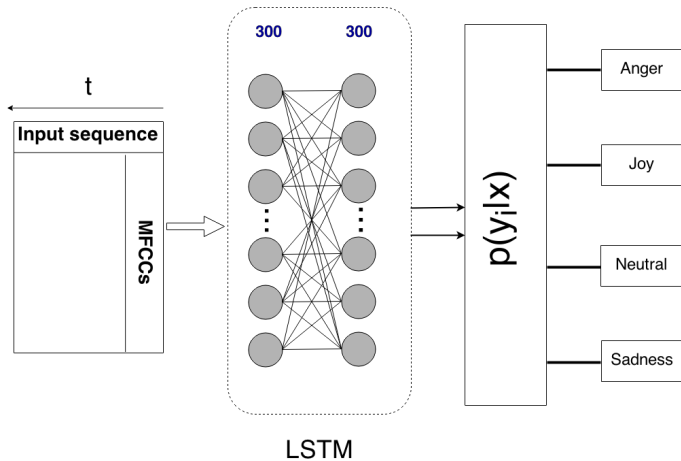
■ CRBM-DNN



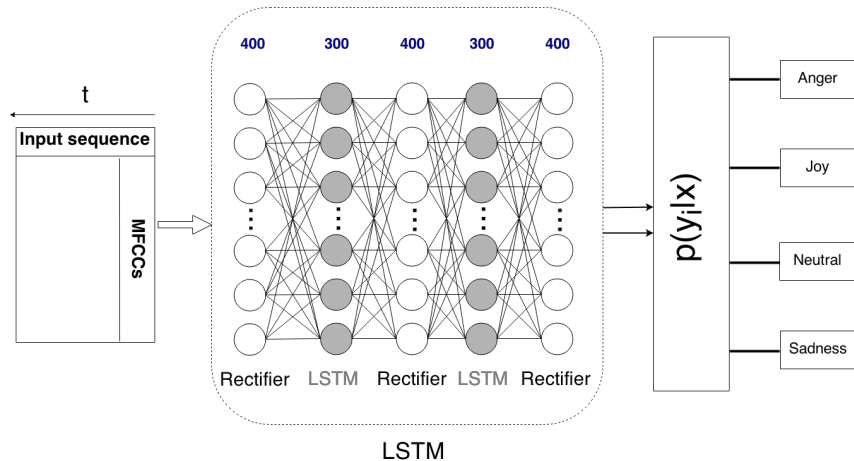
■ CRBM-LSTM



■ LSTM



■ LSTM with rectifier units



Confusion matrix of CRBM-DNN result.

		<i>Classfied</i>			
		Joy	Neutral	Sadness	Anger
<i>True</i>	Joy	57.7%	1.4%	0.0%	40.8%
	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%					

Confusion matrix of CRBM-LSTM result.

		<i>Classified</i>			
		Joy	Neutral	Sadness	Anger
<i>True</i>	Joy	11.3%	9.9%	2.8%	76.1%
	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%					

Confusion matrix of pure LSTM result.

		<i>Classified</i>			
		Joy	Neutral	Sadness	Anger
<i>True</i>	Joy	66.2%	4.2%	0.0%	29.6%
	Neutral	6.3%	79.7%	10.2%	3.8%
	Sadness	0.0%	19.7%	80.3%	0.0%
	Anger	12.6%	0.8%	0.0%	86.6%
recognition rate: 81.59%					

Confusion matrix of LSTM-Rectifier result.

		<i>Classified</i>			
		Joy	Neutral	Sadness	Anger
<i>True</i>	Joy	57.7%	7.0%	0.0%	35.2%
	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%					

Foundations

Conditional Restricted Boltzmann Machine

Restricted Boltzmann Machine

CRBM

Deep Neural Network

Function and Training

Problems and Solutions

Long Short Term Memory

Experiments

Conclusion and Outlook

- Capturing long-term dependencies is necessary for extracting speech emotion
- CRBM-DNN is inappropriate for modelling long-term dependencies (ER: 40.24%)
- LSTM is good at modelling long time dependencies
- Frame-based classification can also reach good result

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

- Capturing long-term dependencies is necessary for extracting speech emotion
- CRBM-DNN is inappropriate for modelling long-term dependencies (ER: 40.24%)
- LSTM is good at modelling long time dependencies
- Frame-based classification can also reach good result
 - CRBM-LSTM 71.98%
 - LSTM 81.59%
 - LSTM with rectifier layers 83.43%

- 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!