Deep Network for Speech Emotion Recognition

—A Study of Deep Learning—

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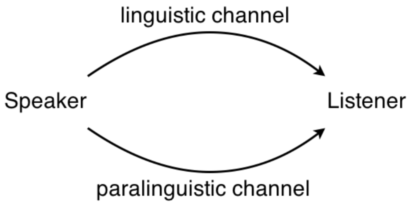
Speech Emotion Recognition

- 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 enoug 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)

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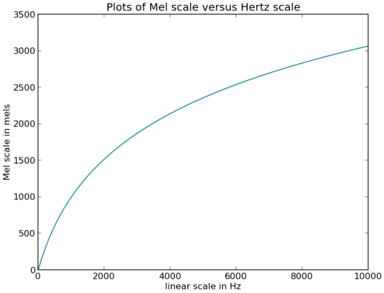
Mel Frequency Cepstral Coefficients

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

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



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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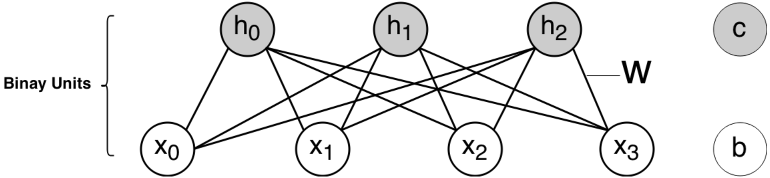
Restricted Boltzmann Machine

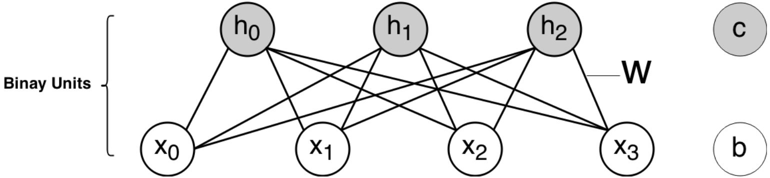
- Generative energy-based graphical model, capture data distrbution $P(\mathbf{x}|\boldsymbol{\theta})$
- Trained in unsupervised way, only use unlabeled input sequence $\mathbf{x}$ for learning.
  - automatically extract useful features from data
  - find hidden structure (distribution).
  - learned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

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

Inference

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

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

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

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

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

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

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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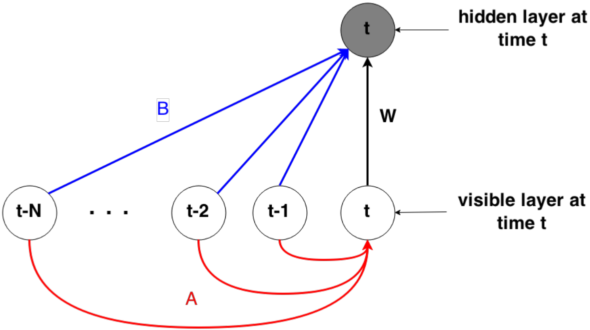

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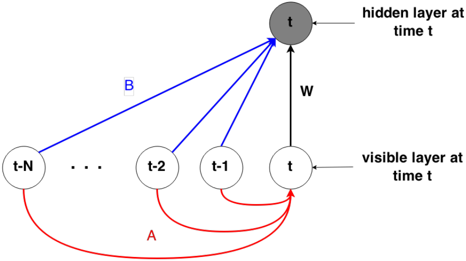

Energy Function: $E_{\boldsymbol{\theta}}^{CRBM}(\mathbf{x}, \mathbf{h}) = \left\| \frac{\mathbf{x} - \tilde{\mathbf{b}}}{2} \right\|^2 - \tilde{\mathbf{c}}^T \mathbf{h} - \mathbf{x}^T \mathbf{W} \mathbf{h}$

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

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

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

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

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Training of Energy-based Model

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

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Kullback-Leibler Divergence:

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

$Q(\mathbf{x})$, 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

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

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

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

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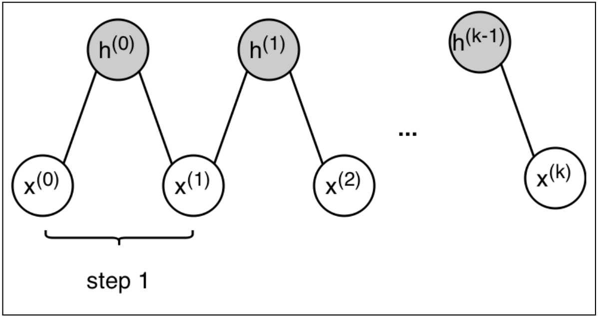
$$\vdots$$

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



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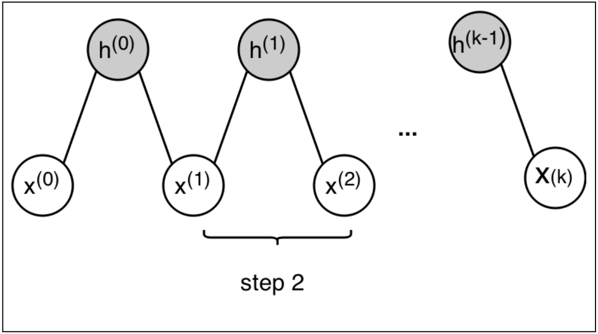

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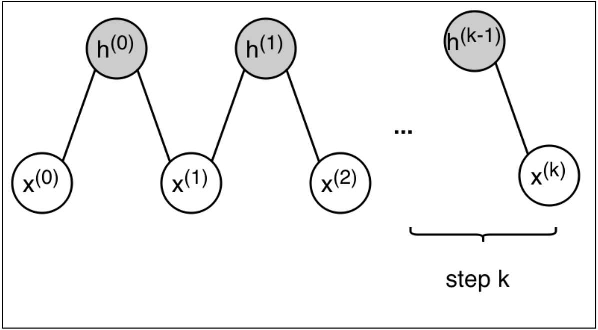

Contrastive Divergence

- 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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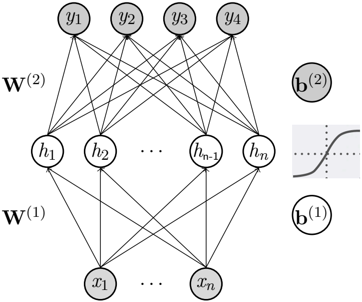
Structure and Function

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

- learning algorithms

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

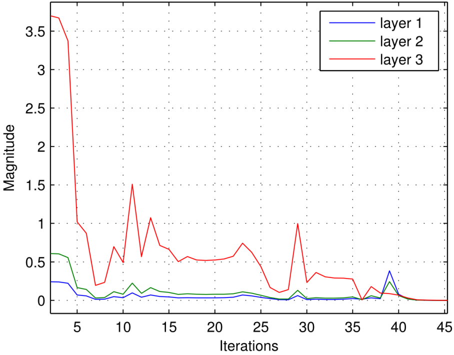
- loss function $l(\hat{y}(\mathbf{x}^{(m)}; \boldsymbol{\theta}), y^{(m)})$
  for sigmoid activation $l(\boldsymbol{\theta}) = \sum_m \frac{1}{2} \left\| y^{(m)} - \hat{y}^{(m)} \right\|^2$
- regularizer $\lambda \Omega(\boldsymbol{\theta})$

Optimization

- Gradient calculation with Backpropagation
- Stochastic/Mini-batch gradient descent

Vanishing Gradient

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



Unsupervised Layerwise Pre-training

Vanishing Gradient

- Training time increases as network gets deeper
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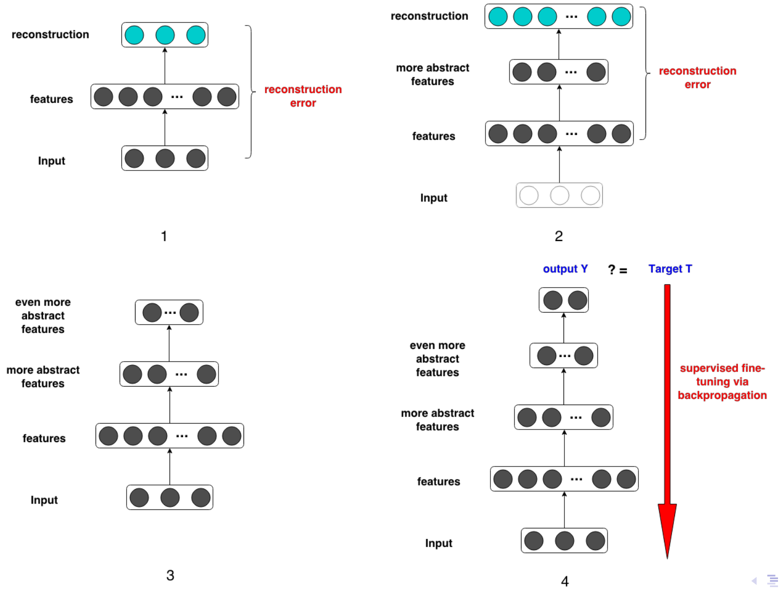
Unsupervised layerwise pre-training

- Pretrain the deep network layer by layer 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

Pre-training



Overfitting

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

Regularization

Overfitting

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Regularization

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

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

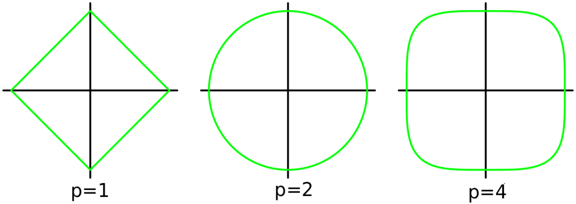
- In convex optimization:

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

P-Norm

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

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



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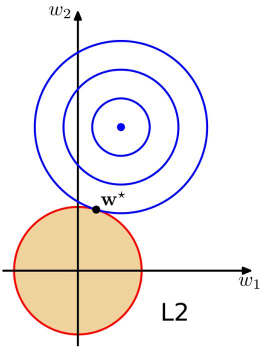

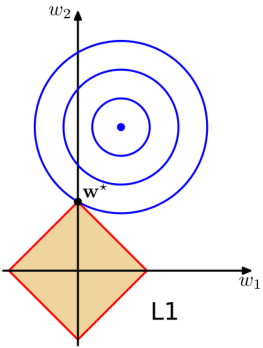

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Problems with RNN

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

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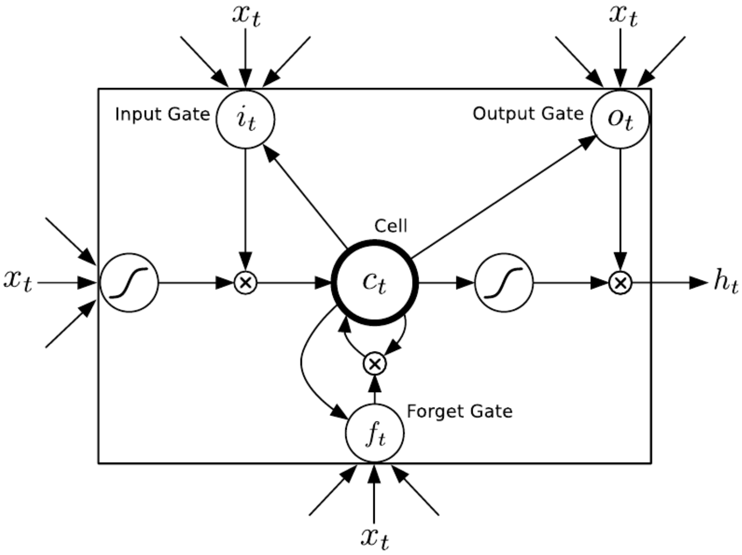
S. Hochreiter and J. Schmidhuber, Lovol. 9, pp. 1735-1780, 1997.

Long short term memory



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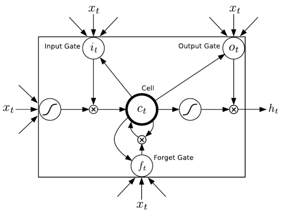
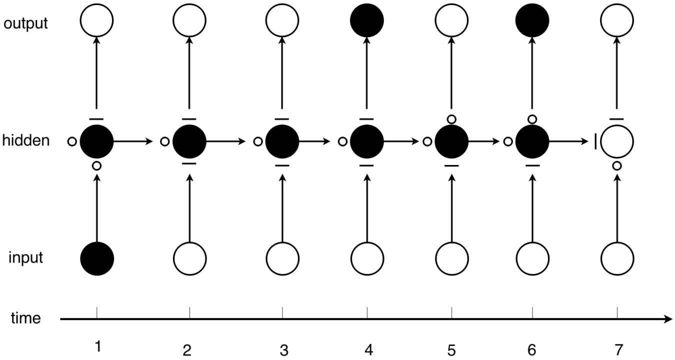


$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i)$$
$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f)$$
$$c_t = f_t c_{t-1} + i_t \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c)$$
$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o)$$
$$h_t = o_t \tanh(c_t)$$

Features in LSTM

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



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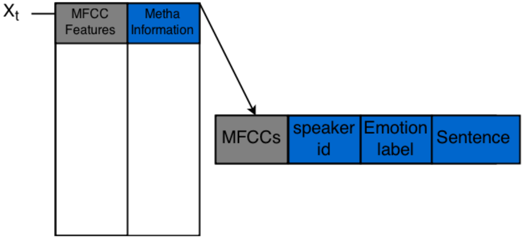
Experiment Setup

EmoDB Database

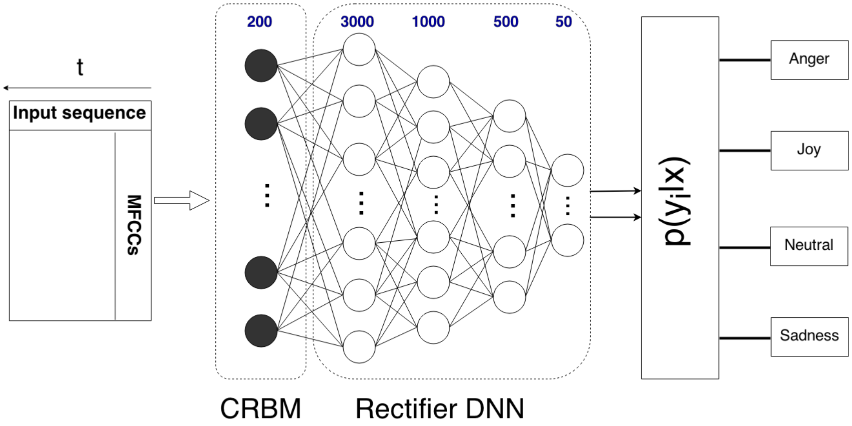
	Joy	Neutral	Sadness	Anger	Total
No. of sentences	71	79	62	127	339
Percent (%)	21	23.2	18.3	37.5	100

Data Structure



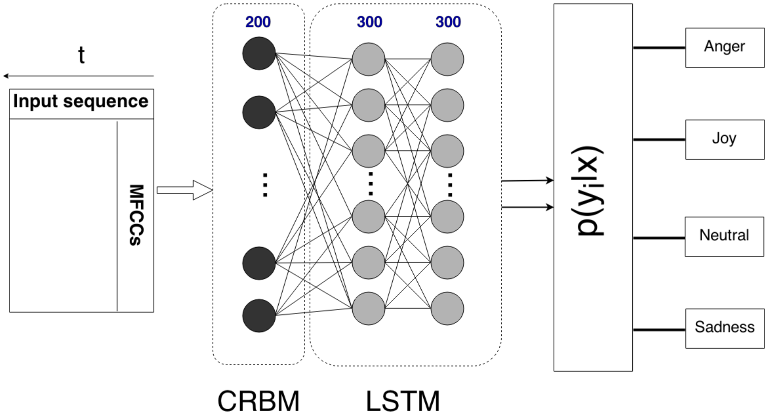
Experiment Setup

- CRBM-DNN



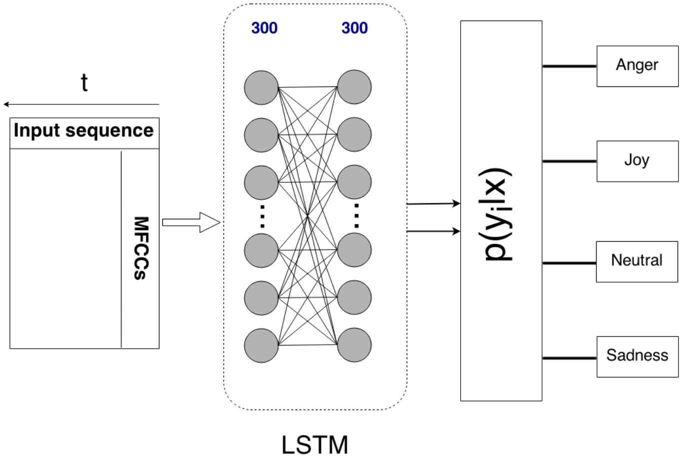
Experiment Setup

- CRBM-LSTM



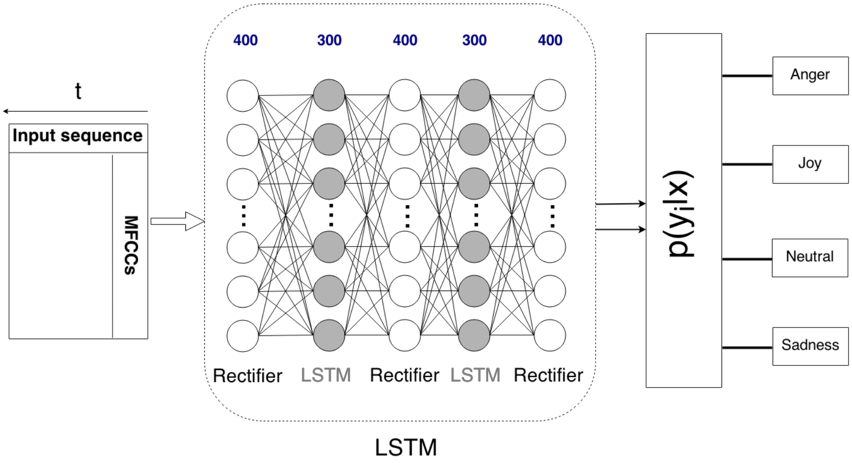
Experiment Setup

- LSTM



Experiment Setup

- LSTM with rectifier units



Result

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%			

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%			

Confusion matrix of pure LSTM result.

		Classfied			
		Joy	Neutral	Sadness	Anger
	Joy	66.2%	4.2%	0.0%	29.6%
True	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%

Result

Confusion matrix of LSTM-Rectifier result.

		Classfied			
		Joy	Neutral	Sadness	Anger
True	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%			

Table of Contents

Conclusion

- 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

Conclusion

- 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

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 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%

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!