Deep Network for Speech Emotion Recognition

—A Study of Deep Learning—

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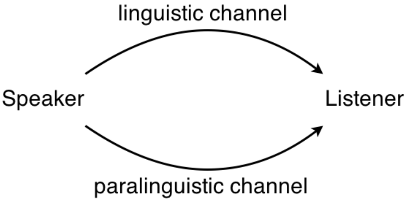
Speech Emotion Recognition

- 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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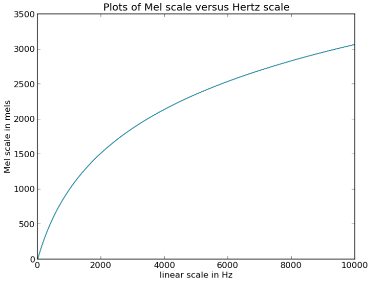
Mel Frequency Cepstral Features

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



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

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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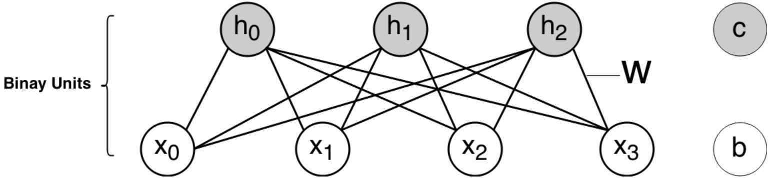
Concepts

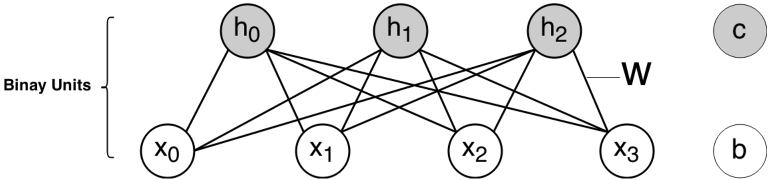
- Generative graphical model, capture data distrbution $P(\mathbf{x}|\boldsymbol{\theta})$
- Trained in unsupervised way, only use unlabeled input sequence$\mathbf{x}$ for learning.
  - automatically extract useful features from data
  - Find hidden structure (distribution).
  - Learned features used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

Restricted Boltzmann Machine

Structure



Structure



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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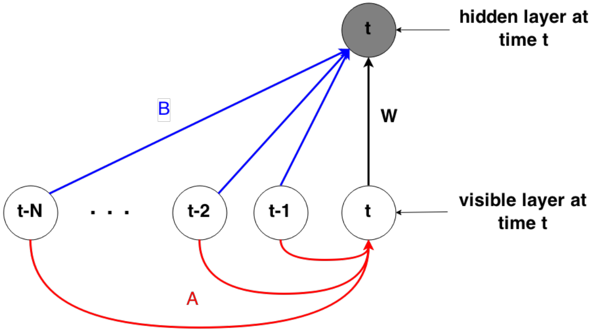
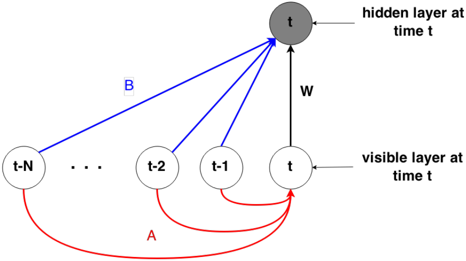


Conditional RBM



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

Kullback-Leibler Divergence:

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

Training of Energy-based Model

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

Free Energy

Training of Energy-based Model

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

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

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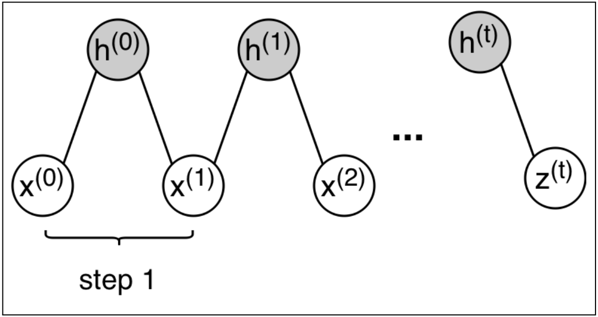
$$-\frac{\partial \log P(\mathbf{x})}{\partial \boldsymbol{\theta}} = \frac{\partial \mathcal{F}(\mathbf{x})}{\partial \boldsymbol{\theta}} - \frac{1}{|\mathcal{N}|} \sum_{\tilde{\mathbf{x}} \in \mathcal{N}} P(\tilde{\mathbf{x}}) \frac{\partial \mathcal{F}(\tilde{\mathbf{x}})}{\partial \boldsymbol{\theta}}$$ sampling

MCMC-Gibbs Sampling

$$\mathbf{x_1} \sim \hat{P}(\mathbf{x})$$

$$\mathbf{h_1} \sim \hat{P}(\mathbf{h}|\mathbf{x}_1)$$



$$\mathbf{x_2} \sim \hat{P}(\mathbf{x}|\mathbf{h}_1)$$

$$\mathbf{h_2} \sim \hat{P}(\mathbf{h}|\mathbf{x}_2)$$

$$\vdots$$

$$\mathbf{x_{t+1}} \sim \hat{P}(\mathbf{x}|\mathbf{h}_t)$$

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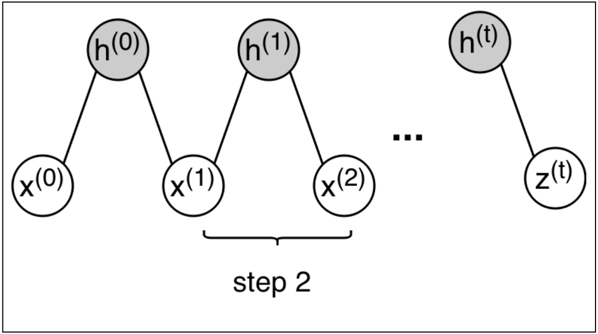

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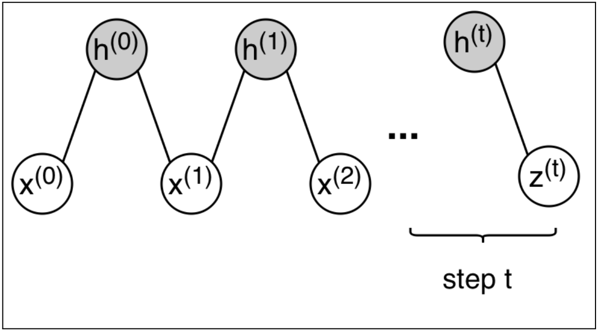

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Contrastive Divergence

$t = 1$, Gibbs step $\rightarrow$ Constrastive Divergence

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N-hidden layers neural network

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

Empirical Risk Minimization

- learning algorithms

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

- loss function $l(\hat{y}(\mathbf{x}^{(m)};\boldsymbol{\theta}), y^{(m)})$

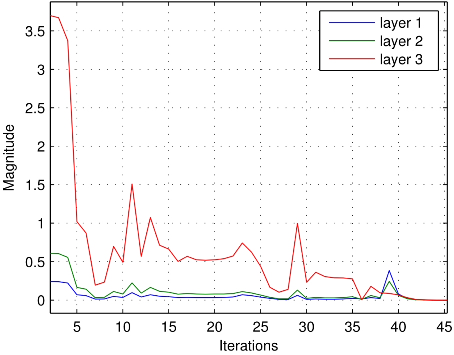
  for sigmoid activation $l(\boldsymbol{\theta}) = \sum_m \frac{1}{2}\left\| y^{(m)} - \hat{y}^{(m)} \right\|^2$
- regularizer $\lambda\Omega(\boldsymbol{\theta})$

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



Pre-training

Vanishing Gradient

- Training time increases as network gets deeper
- Gradient shrink exponentially and training end up local minima
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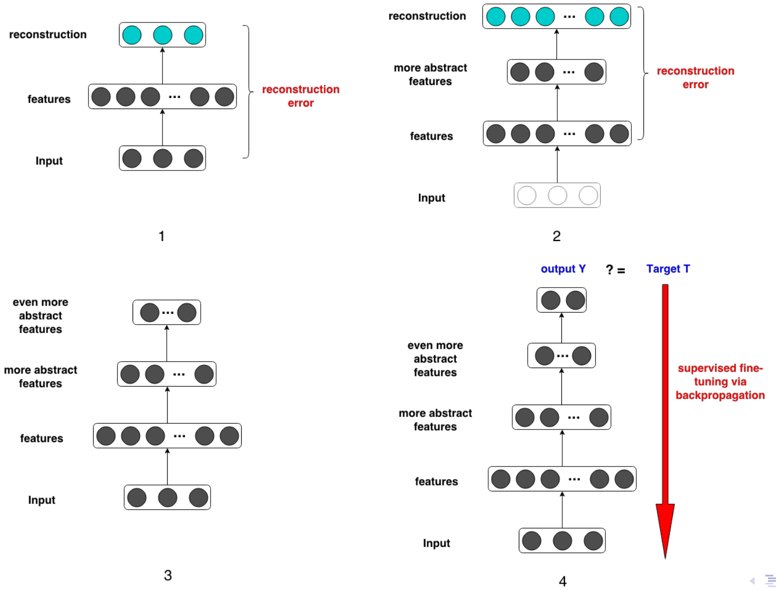
Unsupervised layerwise pre-training

- 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

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Regularization

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

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

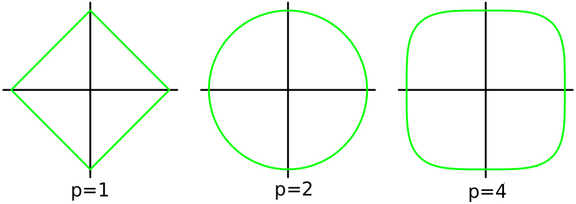
- In convex optimization:

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

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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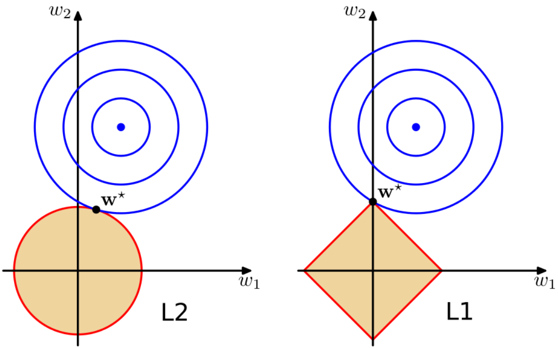

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Concepts of RNN

- 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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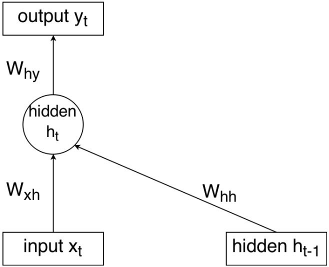
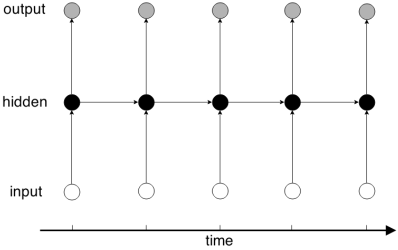
Recurrent Neural Network

Concepts of RNN





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)

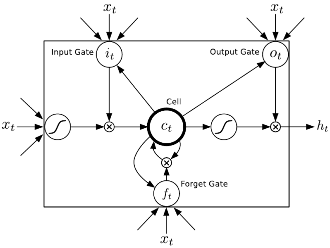
Solutions

-

Long short term memory

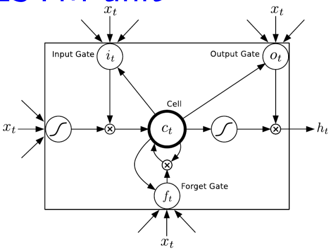
S. Hochreiter and J. Schmidhuber, Lovol. 9, pp. 1735-1780, 1997.

LSTM unit



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

LSTM unit



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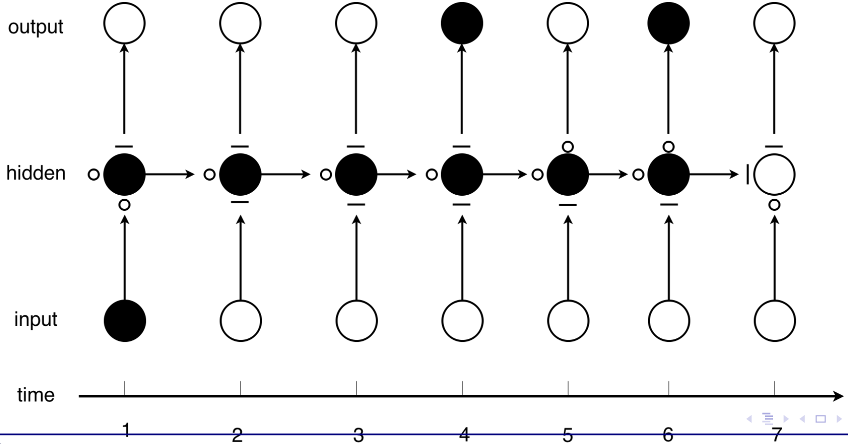
$$

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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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
- Traing CRBM with more/larger data base
- Second order optimization to speed up learning process
- Bi-directional LSTM, capturing future dependencies

Thank You!