Joint Optimisation of Tandem Systems using Gaussian Mixture Density Neural Network Discriminative Sequence Training

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Introduction

Tandem Systems as Mixture Density Neural Networks (MDNNs)
- Tandem systems model features produced by DNN using GMMs
- A bottleneck (BN) DNN and GMMs combine to form an MDNN

Importance of Tandem Systems
- A general framework for modelling non-Gaussian distributions
- Can apply GMM techniques (e.g., adaptation) to improve MDNNs
- Tandem and hybrid systems produce complementary errors

Weakness of Conventional Tandem Systems
- GMMs and DNN are independently estimated → suboptimal
Can Tandem and Hybrid Systems Have Comparable WERs?

Improved Training of Tandem Systems

- Jointly optimise tandem system with MPE or other discriminative sequence criteria
- Can be viewed as MDNN hybrid system MPE training

Proposed Methods

- Adapt extended Baum-Welch (EBW) based GMM MPE training to use stochastic gradient descent (SGD)
- Propose a set of methods to improve joint optimisation stability
Methodology

System Construction Procedure

• Convert GMMs to an MDNN GMM output layer for joint training

Construct a BN DNN to extract tandem features

Build BN GMM-HMMs by Baum-Welch

CE BN DNN

ML Tandem

MPE Joint training of BN DNN + GMMs by SGD

Convert conventional GMMs to a GMM layer

MPE MDNN-HMMs
Methodology

System Refinement and Decoding

- GMM layer is converted back to GMMs to reuse existing facilities

MPE Joint training of BN DNN + GMMs by SGD

Convert the GMM layer to conventional GMMs

Apply GMM-HMM based system refinement

Jointly Trained Tandem
ML Tandem System Construction

- monophone BN GMM-HMMs $\rightarrow$ initial triphone BN GMM-HMMs $\rightarrow$ HMM state clustering $\rightarrow$ final triphone BN GMM-HMMs
GMM Parameter Update Values

- Calculate the partial derivatives of $F$ w.r.t. each GMM parameter and input value
- For SGD, Gaussian component weight and std. dev. values are transformed so constraints satisfied

Speed Up

- Rearrange mean and std. dev. from of Gaussians as matrices
- Speed up GMM calculations by highly optimised general matrix multiplication (GEMM) functions in the BLAS library
MPE Training for GMM-HMMs using SGD

Regularisation

- Parameter smoothing
  - I-smoothing with $\mathcal{F}^{\text{ML}}$: data dependent coeff. $\tau^{\text{ML}}(s, g)$
  - H-criterion with $\mathcal{F}^{\text{MMI}}$: fixed coeff. $\tau^{\text{MMI}}$ (H-criterion)
- L2 regularisation: $\lambda \cdot \theta^2 / 2$
- Composite objective function

$$\mathcal{F}^{\text{MPE}} + \tau^{\text{MMI}}(\mathcal{F}^{\text{MMI}} + \tau^{\text{ML}}(s, g)\mathcal{F}^{\text{ML}}) + \lambda \theta^2 / 2$$

Percentile based Variance Floor

- Modified to find the flooring threshold more efficiently to apply frequently in SGD
Linear to ReLU Activation Function Conversion

- Observe instability issue when averaged partial derivatives w.r.t. linear BN features shifting from positive to negative
- To avoid negative values, modify BN layer bias to equivalently use ReLU by
  \[ b^{bn} - \mu^{bn} + 6 \sigma^{bn} \]

Amplified GMM Learning

- GMMs have a rather different functional form than DNN layers
- Learning rates and L2 reg. coeff. are amplified for GMMs by \( \alpha \)
Relative Update Value Clipping

- To avoid setting a specific threshold for each type of parameter
- Assuming values are Gaussian distributed, compute thresholds of $\Theta$ based on stats. in $n$th mini-batch by

$$\mu_\Theta[n] + m \sigma_\Theta[n]$$

Parameter Update Schemes

- Update GMMs and hidden layers in an interleaved manner
- Update all parameters concurrently without any restriction
- Update all parameters concurrently, then update the GMMs only
Experimental Setup

Data

- 50h and 200h data from ASRU 2015 MGB challenge
- A trigram word level LM with a 160k word dictionary
- `dev.sub` test set contains 5.5h data with reference segmentation and 285 automatic speaker clusters

Systems

- All experiments were conducted with HTK 3.5
- 40-dim log-Mel filter bank features with their $\Delta$ coefficients
- DNN structure $720 \times 1000^5 \times \{4000, 6000\}$
  
  BN DNN structure $720 \times 1000^4 \times 39 \times 1000 \times \{4000, 6000\}$
- Each GMM has 16 Gaussians (sil/sp has 32 Gaussians)
Experimental Results

Comparison of EBW and SGD GMM Training (50h)

- EBW+Smoothing+Var. Floor (Baseline)
- SGD+Fixed Var. Floor
- SGD+Smoothing+Fixed Var. Floor
- SGD+Smoothing+L2+Fixed Var. Floor
- SGD+Smoothing+L2+Var. Floor

Dev.Sub %WER vs Iteration/Epoch Number
Experimental Results

Joint Training Experiments with Different $\alpha$ (50h)

- Concurrent Update + $\alpha=50$
- Concurrent Update + $\alpha=20$
- Concurrent Update + $\alpha=1$
- Interleaved Update + $\alpha=50$
- Extra GMM Epoch

![Graph showing the performance of different update methods over epochs](image-url)
Experimental Results

Comparisons Among Various 50h Systems

- $T_{2}^{50h}$ is comparable to hybrid MPE systems ($H_{1}^{50h}$ & $H_{2}^{50h}$) in both WER and #parameters, and is useful for hybrid system ($H_{4}^{50h}$)

<table>
<thead>
<tr>
<th>ID</th>
<th>System</th>
<th>WER%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{0}^{50h}$</td>
<td>ML BN-GMM-HMMs</td>
<td>38.4</td>
</tr>
<tr>
<td>$T_{1}^{50h}$</td>
<td>MPE BN-GMM-HMMs</td>
<td>36.1</td>
</tr>
<tr>
<td>$T_{2}^{50h}$</td>
<td>MPE MDNN-HMMs</td>
<td>33.8</td>
</tr>
<tr>
<td>$H_{0}^{50h}$</td>
<td>CE DNN-HMMs</td>
<td>36.9</td>
</tr>
<tr>
<td>$H_{1}^{50h}$</td>
<td>MPE DNN-HMMs</td>
<td>34.2</td>
</tr>
<tr>
<td>$H_{2}^{50h}$</td>
<td>MPE DNN-HMMs + $T_{1}^{50h}$ align.</td>
<td>33.7</td>
</tr>
<tr>
<td>$H_{3}^{50h}$</td>
<td>MPE DNN-HMMs + $T_{2}^{50h}$ align.</td>
<td>33.6</td>
</tr>
<tr>
<td>$H_{4}^{50h}$</td>
<td>MPE DNN-HMMs + $T_{2}^{50h}$ align. &amp; tree</td>
<td>33.2</td>
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## Experimental Results

### Comparisons Among Various 200h Systems

- MLLR and joint decoding still improve system performance

<table>
<thead>
<tr>
<th>ID</th>
<th>System</th>
<th>WER%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_0^{200h}$</td>
<td>ML BN-GMM-HMMs</td>
<td>33.7</td>
</tr>
<tr>
<td>$T_1^{200h}$</td>
<td>MPE MDNN-HMMs</td>
<td>29.8</td>
</tr>
<tr>
<td>$T_2^{200h}$</td>
<td>MPE MDNN-HMMs + MLLR</td>
<td>28.6</td>
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<tr>
<td>$H_0^{200h}$</td>
<td>CE DNN-HMMs</td>
<td>31.9</td>
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<tr>
<td>$H_1^{200h}$</td>
<td>MPE DNN-HMMs</td>
<td>29.6</td>
</tr>
<tr>
<td>$H_2^{200h}$</td>
<td>MPE DNN-HMMs + $T_1^{200h}$ align. &amp; tree</td>
<td>29.0</td>
</tr>
<tr>
<td>$J_1^{200h}$</td>
<td>$T_1^{200h} \otimes H_2^{200h}$ joint decoding</td>
<td>28.3</td>
</tr>
<tr>
<td>$J_2^{200h}$</td>
<td>$T_2^{200h} \otimes H_2^{200h}$ joint decoding</td>
<td>27.4</td>
</tr>
</tbody>
</table>
Conclusions

Main Contributions Include

- EBW based GMM-HMM MPE training is extended to SGD
- MDNN discriminative sequence training is studied as tandem system joint optimisation
- A set of methods are modified/proposed to improve training that result in an 6.4% rel. WER reduction over MPE tandem systems

The Jointly Trained Tandem System

- is comparable to MPE hybrid systems in WER and #parameters
- is useful for hybrid system construction and system combination
- can also benefit from existing GMM approaches (e.g., MLLR)
Thanks for listening!