Minimum Phone Error and I-Smoothing for Improved Discriminative Training

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Overview

- MPE Objective Function
- MPE & Other Discriminative Criteria
- Lattice Implementation of MMIE: Review
- Lattice Implementation of MPE
- Optimising the MPE criterion: Extended Baum-Welch
- I-smoothing for Improved Generalization
- Switchboard Experiments
- Summary & Conclusions

MPE Objective Function

- Maximise the following function:

$$\mathcal{F}_{\mathrm{MPE}}(\lambda) = \sum_{r}^{R} \frac{\sum_s p_\lambda(\mathcal{O}_r|s)^\kappa P(s) \mathrm{RawAccuracy}(s)}{\sum_s p_\lambda(\mathcal{O}_r|s)^\kappa P(s)}$$

  where λ are the HMM parameters, $\mathcal{O}_r$ the speech data for file r, κ a probability scale and $P(s)$ the LM probability of s

- $\mathrm{RawAccuracy}(s)$ measures the number of phones correctly transcribed in sentence s (derived from $word$ recognition).
  i.e. the number of correct phones in s $-$ inserted phones in s

- $\mathcal{F}_{\mathrm{MPE}}(\lambda)$ is weighted average of $\mathrm{RawAccuracy}(s)$ over all s

- Scale down log-likelihoods by scale κ. As $\kappa \rightarrow \infty$, criterion approaches phone accuracy on data

- Criterion is to be maximised, not minimised (for compatibility with MMI)

MPE & Other Discriminative Criteria

- MMI maximises the posterior probability of the correct sentence
  Problem: sensitive to outliers, e.g. mistranscribed or confusing utterances
- MCE maximises a smoothed approximation to the sentence accuracy
  Problem: cannot easily be implemented with lattices; scales poorly to long sentences
- Criterion we evaluate in testing is word error rate: makes sense to maximise something similar to it
- MPE uses smoothed approximation to phone error but can use lattice-based implementation developed for MMI
- Note that MPE is an approximation to phone error *in a word recognition context* i.e. uses word-level recognition, but scoring is on a phone error basis.
- Can directly maximise a smoothed *word* error rate → Minimum Word Error (MWE). Performance for MWE slightly worse than MPE, so main focus here on MPE

Lattice Implementation of MMI: Review

- Generate lattices marked with time information at HMM level
  - Numerator (num) from correct transcription
  - Denominator (den) from confusable hypotheses from recognition
- Use Extended Baum-Welch (Gopalakrishnan et al, Normandin) updates e.g. for means

$$\hat{\mu}_{jm} = \frac{\left\{\theta^{\mathrm{num}}_{jm}(\mathcal{O}) - \theta^{\mathrm{den}}_{jm}(\mathcal{O})\right\} + D\mu_{jm}}{\left\{\gamma^{\mathrm{num}}_{jm} - \gamma^{\mathrm{den}}_{jm}\right\} + D}$$

  - Gaussian occupancies (summed over time) are γ_{jm} from forward-backward
  - $\theta_{jm}(\mathcal{O})$ is sum of data, weighted by occupancy.
- For rapid convergence use Gaussian-specific D-constant
- For better generalisation broaden posterior probability distribution
  - Acoustic scaling
  - Weakened language model (unigram)

Lattice Implementation of MPE

- Problem: $\mathrm{RawAccuracy}(s)$, defined on sentence level as (#correct - #inserted) requires alignment with correct transcription

- Express $\mathrm{RawAccuracy}(s)$ as a sum of $\mathrm{PhoneAcc}(q)$ for all phones q in the sentence hypothesis s:

$$\mathrm{PhoneAcc}(q) = \left\{ \begin{array}{l} 1 \text{ if correct phone} \\ 0 \text{ if substitution} \\ -1 \text{ if insertion} \end{array} \right\}.$$

- Calculating $\mathrm{PhoneAcc}(q)$ still requires alignment to reference transcription

- Use an approximation to $\mathrm{PhoneAcc}(q)$ based on time-alignment information
  - compute the proportion e that each hypothesis phone overlaps the reference
  - gives a lower-bound on true value of $\mathrm{RawAccuracy}(s)$

Approximating PhoneAcc using Time Information

$$\text{PhoneAcc}(q) = \left\{ \begin{array}{l} -1 + 2e \text{ if same phone} \\ -1 + e \text{ if different phone} \end{array} \right\}$$

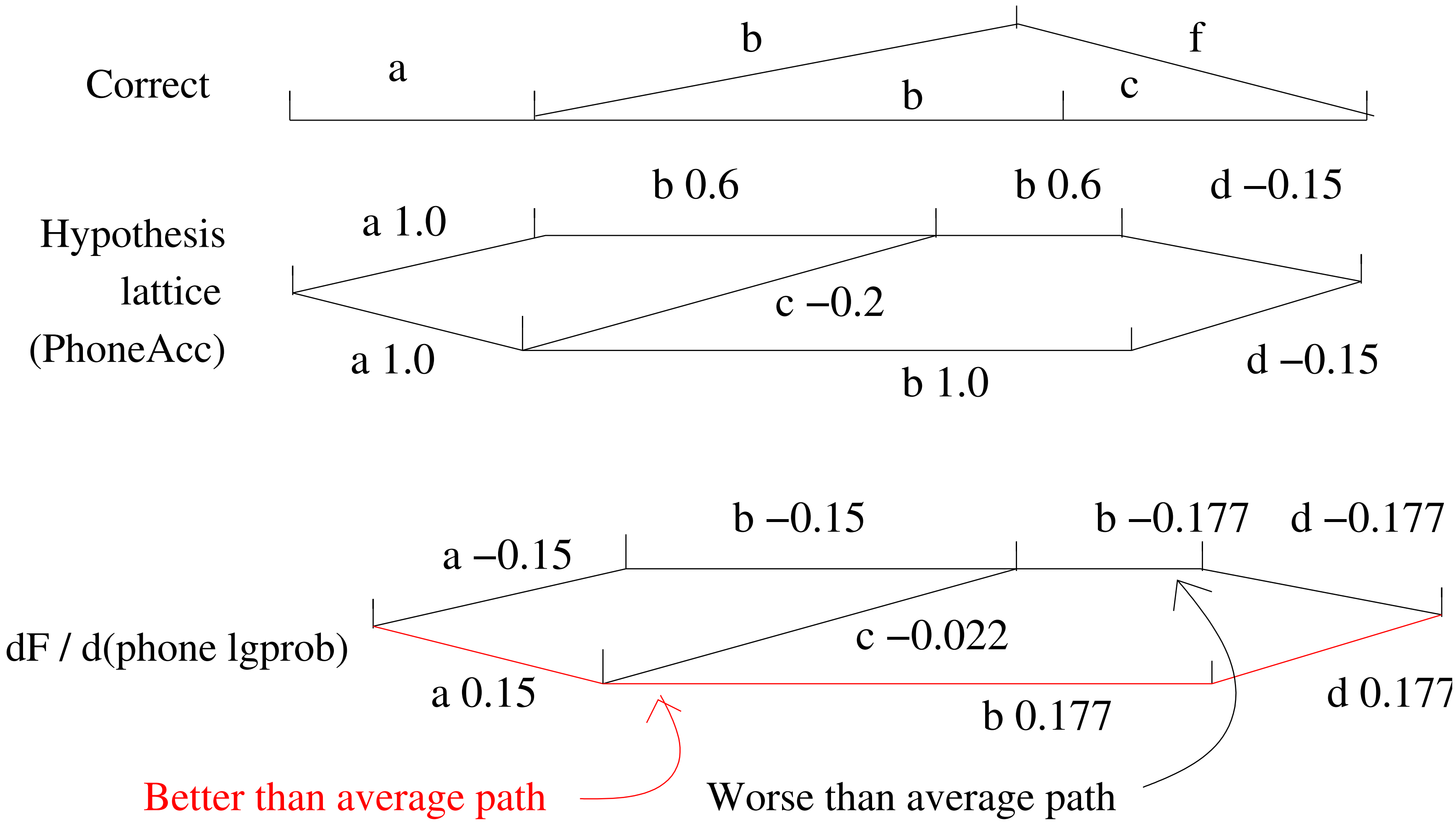
Reference	a	b			c
Hypothesis	a	b	b		d
Proportion e	1.0	0.8	0.2	0.15	0.85
–1 + (correct:2*e, incorrect:e)	1.0	0.6	–0.6	–0.85	–0.15
Max of above	1.0	0.6	–0.6		–0.15

Approximated sentence raw accuracy from above = 0.85

Exact value of raw accuracy: 2 corr – 1 ins = 1

PhoneAcc Approximation For Lattices

Calc $\mathrm{PhoneAcc}(q)$ for each phone q, then find $\frac{\partial \mathcal{F}_{\mathrm{MPE}}(\lambda)}{\partial \log p(q)}$ (forward-backward)



Applying Extended Baum-Welch to MPE

- Use EBW update formulae as for MMI but with modified MPE statistics
- For MMI, the occupation probability for an arc q equals $\frac{1}{\kappa}\frac{\partial \mathcal{F}_{\mathrm{MMIE}}(\lambda)}{\partial \log p(q)}$ for numerator ($\times -1$ for the denominator). The denominator occupancy-weighted statistics are subtracted from the numerator in the update formulae
- Statistics for MPE update use $\frac{1}{\kappa}\frac{\partial \mathcal{F}_{\mathrm{MPE}}(\lambda)}{\partial \log p(q)}$ of the criterion w.r.t. the phone arc log likelihood which can be calculated efficiently
- Either MPE numerator or denominator statistics are updated depending on the sign of $\frac{\partial \mathcal{F}_{\mathrm{MPE}}(\lambda)}{\partial \log p(q)}$, which is the "MPE arc occupancy"
- After accumulating statistics, apply EBW equations
- EBW is viewed as a gradient descent technique and can be shown to be a valid update for MPE.

Improved Generalisation using I-smoothing

- Use of discriminative criteria can easily cause over-training
- Get smoothed estimates of parameters by combining Maximum Likelihood (ML) and MPE objective functions for each Gaussian
- Rather than globally interpolate (H-criterion), amount of ML depends on the occupancy for each Gaussian
- I-smoothing adds τ samples of the average ML statistics for each Gaussian. Typically $\tau = 50$.
  - For MMI scale numerator counts appropriately
  - For MPE need ML counts in addition to other MPE statistics
- I-smoothing essential for MPE (& helps a little for MMI)

Experimental Setup

- PLP cepstral features + first/second derivatives (39 dims)
- Cepstral mean/variance normalisation
- Vocal tract length normalisation
- Training on h5train00 (265 hours) or h5train00sub (68 hours)
- Decision tree-clustered triphone HMMs with 6165 states
  - 16 mix comps for h5train00
  - 12 mix comps for h5train00sub
- Testing on 1998 Hub5 evaluation data: about 3 hours (Swbd2/Call Home)
- Need more training iterations for MPE than MMI (e.g. 8 vs 4)

Switchboard Results (I)

	% WER Train	% WER eval98	% WER redn (test)
MLE	41.8	46.6	–
MMIE	30.1	44.3	2.3
MMIE (τ=200)	32.2	43.8	2.8
MPE (τ=50)	27.9	43.1	3.5

HMMs trained on h5train00sub (68h train). Train use lattice unigram

	% WER Train	% WER eval98	% WER redn (test)
MLE baseline	47.2	45.6	–
MMIE	37.7	41.8	3.8%
MMIE (τ=200)	35.8	41.4	4.2%
MPE (τ=100)	34.4	40.8	4.8%

HMMs trained on h5train00 (265h train). Train is lattice unigram

- I-smoothing reduces the error rate with MMI by 0.3-0.4% abs
- MPE/I-smoothing gives around 1% abs lower WER than previous MMI results

Switchboard Results (II)

	% WER Train	% WER eval98	% WER redn (test)
MLE	41.8	46.6	–
MPE ($\tau = 0$)	28.5	50.7	-4.1%
MPE ($\tau = 25$)	27.9	43.1	3.5%
MWE ($\tau = 25$)	25.9	43.3	3.3%

HMMs trained on h5train00sub (68h train). Train use lattice unigram

- Training set WER reduces with/without I-smoothing
- I-smoothing essential for test-set gains with MPE
- Minimum Word Error (MWE) better than MPE on train
- MWE generalises less well than MPE

Summary & Conclusions

- Introduced MPE (& MWE) to give error-rate based discriminative training
  - Less affected by outliers than MMI-based training
  - Smoothed approximation to phone error in word recognition system
  - Approximate reference-hypothesis alignment
  - Use same lattice-based training framework developed for MMI
  - Compute suitable MPE statistics so still use Extended Baum-Welch update
  - Use I-smoothing to improve generalisation (essential for MPE)

- MPE/I-smoothing reduces WER over previous MMI approach by 1% abs

- MPE used for CU-HTK April 2002 Switchboard evaluation system