Hypothesis Posterior Student-Teacher Training

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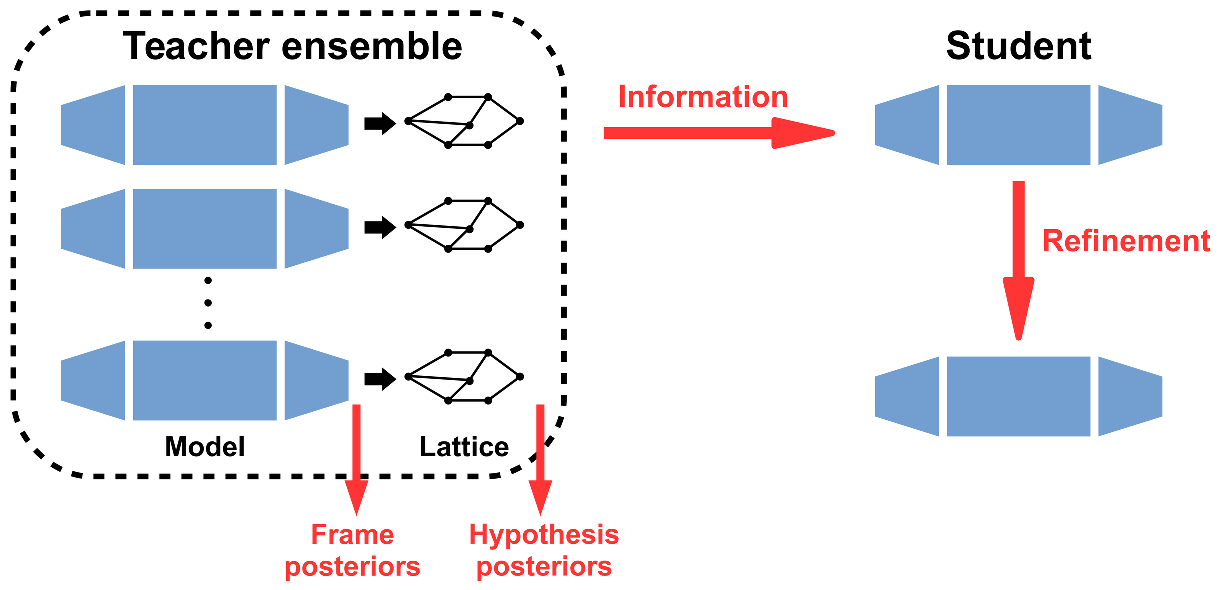
1 INTRODUCTION

- Ensemble methods
  - improve ASR performance
  - are computationally expensive to decode.
- Student-Teacher (S-T) training
  - trains single student model to emulate teacher ensemble.
  - Existing methods only transfer frame posterior information.
- This work incorporates sequence discriminative criteria into S-T training by:
  - sequence discriminative training of the teacher ensemble
  - further sequence discriminative training of the student model after frame-level S-T training
  - a proposed hypothesis-level S-T criterion.



2 TEACHER ENSEMBLE

- Diversity obtained by
  - different DNN random initialisations.
- Teachers can be trained using the following criteria:
  - Cross-Entropy (CE)

$$\mathcal{F}_{\text{CE}} = -\sum_r \sum_t \sum_{s_{rt}} \delta\left(s_{rt}, s^*_{rt}\right) \log P\left(s_{rt} | \boldsymbol{o}_{rt}, \boldsymbol{\Phi}_m\right)$$

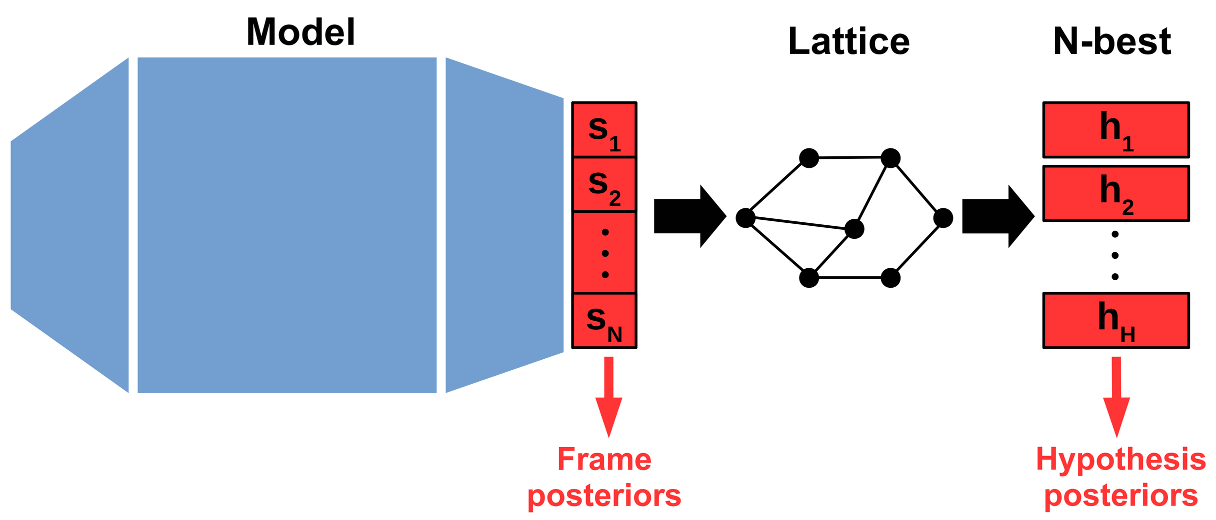
  - Maximum Mutual Information (MMI)

$$\mathcal{F}_{\text{MMI}} = -\sum_r \sum_{h_r} \delta\left(h_r, h^*_r\right) \log P\left(h_r | \mathbf{O}_r, \boldsymbol{\Phi}_m\right)$$

  - state-level Minimum Bayes Risk (sMBR)

$$\mathcal{F}_{\text{sMBR}} = \sum_r \sum_{h_r} L\left(h_r, h^*_r\right) P\left(h_r | \mathbf{O}_r, \boldsymbol{\Phi}_m\right).$$

3 INFORMATION PROPAGATION



- Frame posteriors
  - Existing method.
  - Minimise KL-divergence between frame posteriors.
  - Interpolate with hard alignments.

$$\mathcal{C}_{\text{CE}} = -\sum_r \sum_t \sum_{s_{rt}} \left[(1-\lambda)\, \delta\left(s_{rt}, s^*_{rt}\right) + \lambda \sum_m \alpha_m P\left(s_{rt} | \boldsymbol{o}_{rt}, \boldsymbol{\Phi}_m\right) \right] \log P\left(s_{rt} | \boldsymbol{o}_{rt}, \boldsymbol{\Theta}\right).$$

  - Setting $\lambda = 0$ reduces to CE.
- Hypothesis posteriors
  - Novel approach.
  - Minimise KL-divergence between hypothesis posteriors.
  - Interpolate with manual transcriptions.

$$\mathcal{C}_{\text{MMI}} = -\sum_r \sum_{h_r} \left[(1-\eta)\, \delta\left(h_r, h^*_r\right) + \eta \sum_m \beta_m P\left(h_r | \mathbf{O}_r, \boldsymbol{\Phi}_m\right) \right] \log P\left(h_r | \mathbf{O}_r, \boldsymbol{\Theta}\right).$$

  - Setting $\eta = 0$ reduces to the MMI criterion.

4 EXPERIMENTS

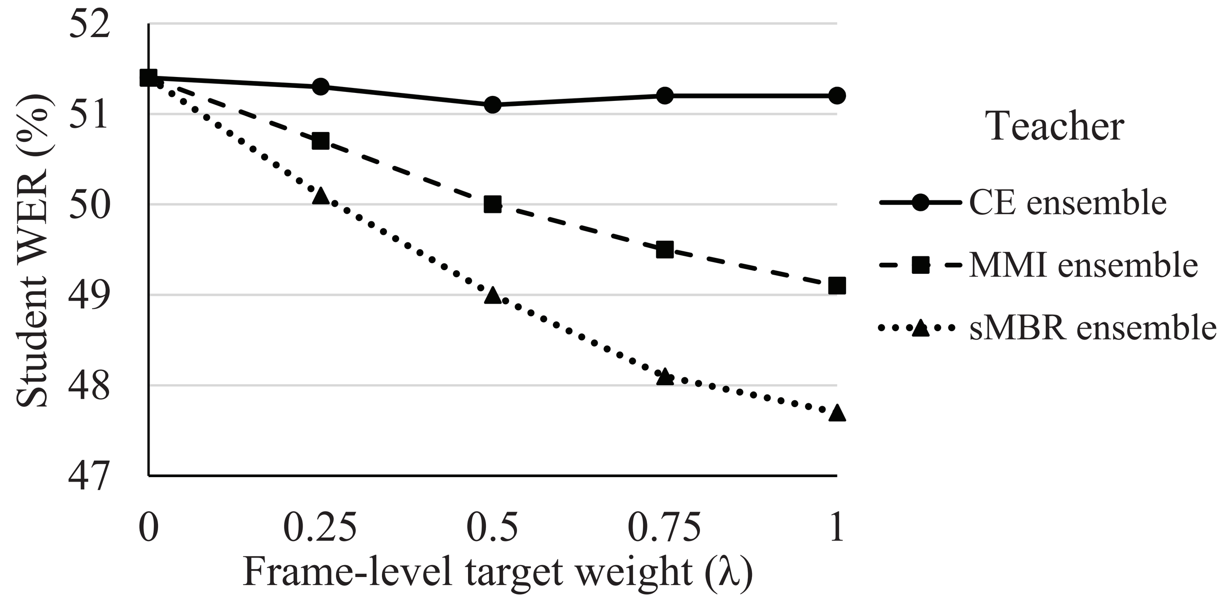
- Datasets:
  - IARPA Babel Tok Pisin (*IARPA-babel207b-v1.0e*)
    - 3 hour VLLP training set
    - 10 hour development set
  - WSJ
    - 14 hour *si-84* training set
    - 64K words open-vocabulary *eval92* test set.
- Setup:
  - **Ensemble size** = 10 (Tok Pisin), 4 (WSJ)
  - **Combination method** = MBR combination decoding
  - **Acoustic model** = DNN-HMM hybrid
    - 1000 nodes × 4 layers for Tok Pisin
    - 2000 nodes × 6 layers for WSJ.
- The student and teacher models have the same architecture.

4.1 TEACHER ENSEMBLE TRAINING CRITERION

- Training ensemble with different criteria, in Tok Pisin

Ensemble criterion	Single system WER (%) mean	best	worst	std dev	Combined WER (%)
CE	51.4	51.3	51.5	0.1	50.5
MMI	49.3	49.1	49.4	0.1	48.4
sMBR	48.2	48.1	48.4	0.1	47.0

  - Training teachers with sequence discriminative criteria improves combined ensemble performance.
- Frame-level S-T training with sequence-trained teachers, in Tok Pisin



  - Gains from sequence discriminative training of teachers are carried through to student.
  - $\lambda = 1$ produces the best student performances for sequence-trained teacher ensembles.

4.2 REFINEMENT OF THE STUDENT MODEL

Training	WER (%) Tok Pisin	WSJ
frame level S-T	47.7	5.07
frame level S-T + MMI	47.6	5.09
frame level S-T + sMBR	47.2	4.94

- Student is initialised using frame-level S-T training with the sMBR-trained teacher ensemble.
- For WSJ,
  - **mean single sMBR system WER** = 5.09 %
  - **combined ensemble WER** = 4.84 %.
- Further sMBR training of student improves performance.
- Further MMI training does not give significant gains, as the teacher ensemble has been sMBR-trained.

4.3 PROPAGATING HYPOTHESIS POSTERIOR INFORMATION

Training	η	WER (%) Tok Pisin	WSJ
frame level S-T	-	47.7	5.07
frame level S-T + MMI	0.0	47.6	5.09
hypothesis level S-T	0.5	47.0	4.91
hypothesis level S-T	1.0	47.4	4.94

- Hypothesis-level S-T training improves the student performance beyond frame-level S-T training, even with further MMI training.

5 CONCLUSIONS

- Sequence discriminative training of the teacher ensemble improves the resulting student performance.
- Further sequence discriminative training after frame-level S-T training brings additional gains.
- Proposed hypothesis-level S-T training yields gains over frame-level S-T training, even with further sequence discriminative training.

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