Semi-supervised Maximum Mutual Information Training of Deep Neural Network Acoustic Models

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Outline

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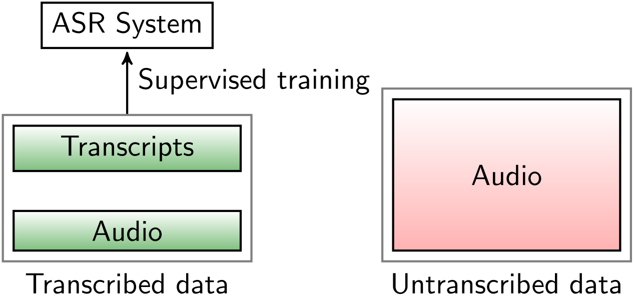
Speech Data



- Audio: Spectral features extracted from wav files
- Transcription: Word sequences (subtitles)

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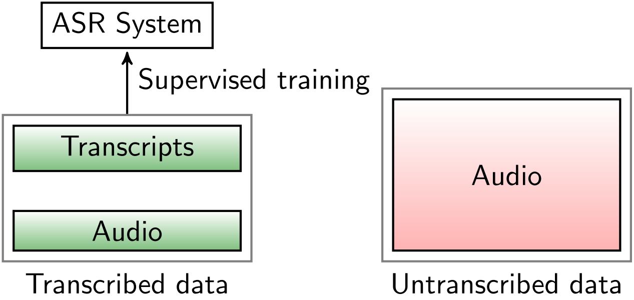

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- Why do we want to use untranscribed data?

Outline

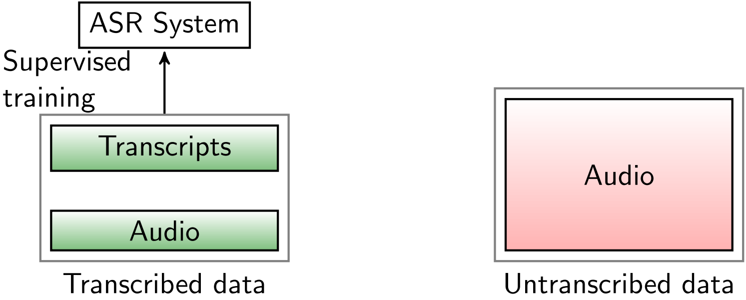
Unsupervised Approaches - Motivations

Why do we want to use untranscribed data?

- Availability of exponentially large amounts of untranscribed acoustic data
- Interests in speech recognition in low-resource languages
- Test data changes with time.

Unsupervised Approaches - Self-training

- Self-training: Use a seed model trained on transcribed data to transcribe the audio



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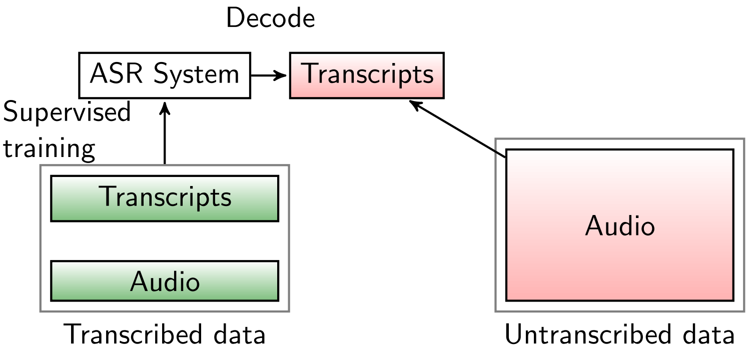

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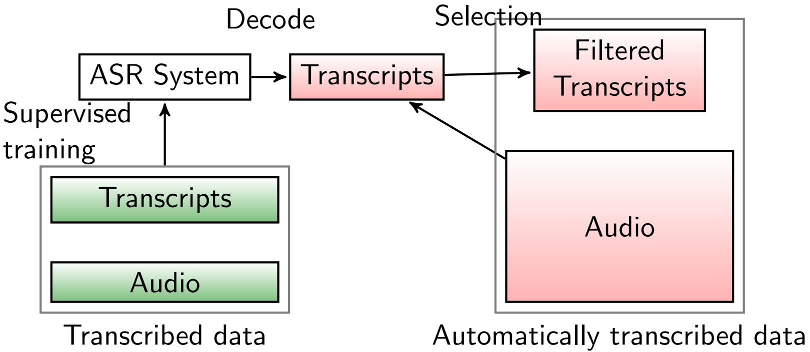

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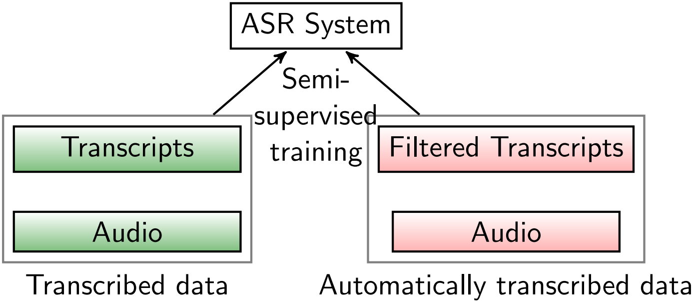

Unsupervised Approaches - Self-training

- Data selection can involve:
  - Confidence-based filtering to select 'good' data
  - Confidence-based weighting
- Sentence-level scores, word-level scores, frame-level scores etc.

Unsupervised Approaches - Self-training

Problem

The decision for using the data (filtering or weighting) is done before training, and not incorporated in the training process.

Solution

Incorporate confidences into the objective function

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Acoustic Model

Basic Speech Recognition problem:

- Given an acoustic feature sequence O, find the transcript (word sequence) W that best describes it.

$$\begin{aligned}\hat{W} &= \arg\max_{W \in \mathcal{H}} P(W \mid O) \\ &= \arg\max_{W \in \mathcal{H}} P_A(O \mid W) P_L(W) \qquad (1)\end{aligned}$$

where
$P_A(O \mid W)$ is called the Acoustic Model,
$P_L(W)$ is called the Language Model

Acoustic Model

- Labelled training data $(\mathcal{D}_{\mathcal{L}})$: L utterances with
  - Acoustic features - $\mathbf{O}^{(1)}, \mathbf{O}^{(2)} \ldots \mathbf{O}^{(L)}$
  - Corresponding transcripts - $W^{(1)}, W^{(2)} \ldots W^{(L)}$
- Maximum Likelihood Estimation

$$\mathcal{F}_{\mathrm{ML}}(\lambda) = \sum_{r=1}^{L} \log P_A(\mathbf{O}^{(r)} \mid W^{(r)}; \lambda) \tag{2}$$

- Maximum Mutual Information Estimation

$$\mathcal{F}_{\mathrm{MMI}}(\lambda) = \mathbb{I}(\mathbf{O} : W) \tag{3}$$

Maximum Mutual Information (MMI)

$$
\begin{aligned}
\mathcal{F}_{\mathrm{MMI}}(\lambda) &= \mathbb{I}(\mathbf{O}; W) \\
&= \frac{1}{L} \sum_{r=1}^{L} \log \frac{P(\mathbf{O}^{(r)}, W^{(r)})}{P(\mathbf{O}^{(r)}) P(W^{(r)})} \quad \text{(Empirical MI)} \\
&\propto \frac{1}{L} \sum_{r=1}^{L} \log P(W^{(r)} \mid \mathbf{O}^{(r)}) \quad \text{(Conditional Likelihood)} \\
&\propto \frac{1}{L} \sum_{r=1}^{L} \log \frac{P_A(\mathbf{O}^{(r)} \mid W^{(r)})}{\sum_{W'} P_A(\mathbf{O}^{(r)} \mid W') P_L(W')}
\end{aligned}
$$

Log-likelihood under the reference transcript − Log-likelihood under all possible transcripts.

Discriminative Training

$$\begin{array}{c} \text{Log-likelihood under} \\ \text{the reference transcript} \end{array} - \begin{array}{c} \text{Log-likelihood under} \\ \text{all possible transcripts.} \end{array}$$

Problem

- Standard discriminative training is very sensitive to the accuracy of the transcripts (Mathias et al. [2005]).
- So self-training methods do not work very well with discriminative training.

Solution

As before, we modify the objective function.

Discriminative Training

- Discriminative training tries to make the model maximally discriminative of the reference transcript against the competing hypotheses.

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Maximum Mutual Information (MMI)

- Transcribed data – Conditional Likelihood

$$\mathcal{F}_{\mathrm{MMI}}(\lambda) = \frac{1}{L}\sum_{r=1}^{L} \log \mathbb{P}(W^{(r)} \mid \mathbf{O}^{(r)})$$

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$$\mathcal{F}_{\mathrm{MMI}}(\lambda) = \frac{1}{L}\sum_{r=1}^{L} \log \mathbb{P}(W^{(r)} \mid \mathbf{O}^{(r)})$$

- Automatically transcribed data – Conditional Likelihood

$$\mathcal{F}_{\mathrm{MMI}}(\lambda) = \frac{1}{U}\sum_{r=1}^{U} \sum_{W} \mathbb{P}(W \mid \mathbf{O}^{(r)}) \log \mathbb{P}(W^{(r)} \mid \mathbf{O}^{(r)})$$

$$= -\sum_{r=1}^{U} \mathbb{H}(W \mid \mathbf{O}^{(r)}; \lambda)$$

Maximum Mutual Information (MMI)

- Transcribed data – Conditional Likelihood

$$\mathcal{F}_{\mathrm{MMI}}(\lambda) = \frac{1}{L}\sum_{r=1}^{L} \log \mathbb{P}(W^{(r)} \mid \mathbf{O}^{(r)})$$

- Untranscribed data – Negative Conditional Entropy

$$\mathcal{F}_{\mathrm{NCE}}(\lambda) = \frac{1}{U}\sum_{r=1}^{U} \sum_{W} \mathbb{P}(W \mid \mathbf{O}^{(r)}) \log \mathbb{P}(W \mid \mathbf{O}^{(r)})$$

$$= -\sum_{r=1}^{U} \mathbb{H}(W \mid \mathbf{O}^{(r)}; \lambda)$$

Lattice Entropy

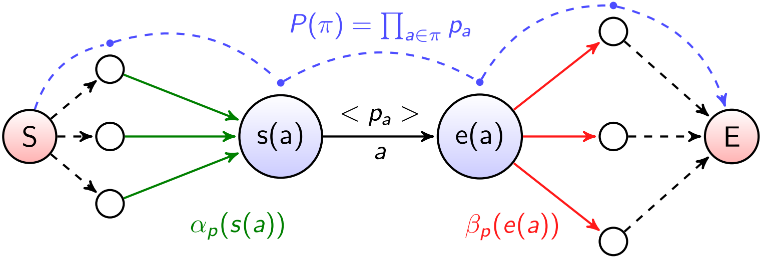
- Take weighted average over all possible hypotheses in the lattice

$$\mathcal{F}_{\mathrm{NCE}}(\lambda) = \sum_{r=1}^{U} \sum_{W} \mathbb{P}(W \mid \mathbf{O}^{(r)}; \lambda) \log \mathbb{P}(W \mid \mathbf{O}^{(r)}; \lambda)$$
$$= -\sum_{r=1}^{U} \mathbb{H}(W \mid \mathbf{O}^{(r)}; \lambda)$$

- This is exactly minimizing the lattice entropy.
- Minimizing lattices entropy makes the model more confident of one of the hypotheses.

Lattice Entropy – Forward-Backward

- Forward-backward algorithm[1] over the lattice using WFSTs
- $Z = \sum_{\pi \in \mathcal{L}} P(\pi)$



$$\alpha_p(s) = \sum_{s'} \alpha_p(s') p_{s's} \qquad \beta_p(s) = \sum_{s'} \beta_p(s') p_{s's}$$

[1] Li and Eisner [2009], Huang [2012]

Lattice Entropy – WFST

$$\mathcal{F}_{\mathrm{NCE}}(\lambda) = \sum_{r=1}^{U} \sum_{W} \mathbb{P}(W \mid \mathbf{O}^{(r)}; \lambda) \log \mathbb{P}(W \mid \mathbf{O}^{(r)}; \lambda)$$

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- Do forward-backward, but with a new semiring.
- Replace p_a with a pair $< p_a, p_a \log p_a >$.

Operation	Value
$< p_1, p_1 \log p_1 > \otimes < p_2, p_2 \log p_2 >$	$< p_1 p_2, p_1 p_2 \log p_2 + p_2 p_1 \log p_1 >$
$< p_1, p_1 \log p_1 > \oplus < p_2, p_2 \log p_2 >$	$< p_1 + p_2, p_1 \log p_1 + p_2 \log p_2 >$
Zero()	$< 0, 0 >$
One()	$< 1, 0 >$

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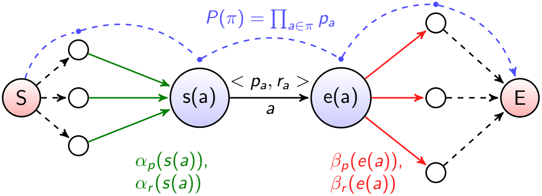

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Lattice Entropy – Gradients

$$H_{\mathcal{L}} = -\sum_{\pi \in \mathcal{L}} P(\pi) \log P(\pi)$$

$$\nabla H_{\mathcal{L}} = ??$$

- We have used a Forward-Backward to compute the objective function.
- But we need derivatives of the objective function.
- Another pass over lattice.
- The derivatives are aggregated over the arcs for each context-dependent state and then backpropagated through the DNN.

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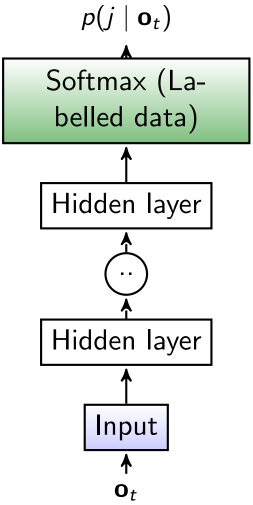
1. Introduction
2. Unsupervised Training
3. Discriminative training
   - Maximum Mutual Information (MMI)
   - Lattice Entropy
   - Lattice computations
4. Deep Neural Network
   - Baseline
   - Multilingual-inspired architecture
   - DNN Priors
5. Experiments

Deep Neural Network - CE Supervised training

- $\mathcal{D}_\mathcal{L} = \{(\mathbf{O}^{(r)}, W^{(r)})_{r=1}^{L}\}$
- Word sequences $W^{(r)}$ are converted to frame-alignment using Viterbi alignment
- For each frame t, we have a context-dependent phone j
- $\mathcal{D}_\mathcal{L} = \{(\mathbf{o}_t, \mathbf{z}_t) : t \in \{1 \cdots N_L\}\}$

$$\mathcal{F}_{\mathrm{CE}} = -\sum_t \sum_{j=1}^{K} z_{tj} \log p(j \mid \mathbf{o}_t) \tag{4}$$



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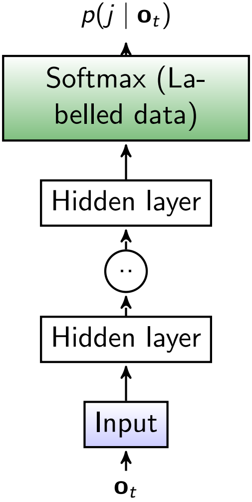

Deep Neural Network - CE Self-training

Viterbi alignment

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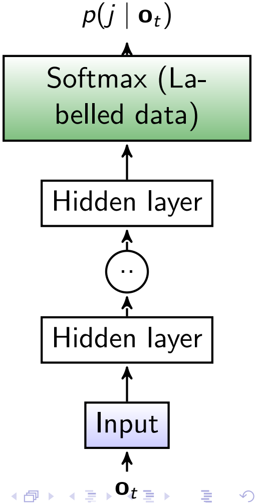

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Viterbi decode

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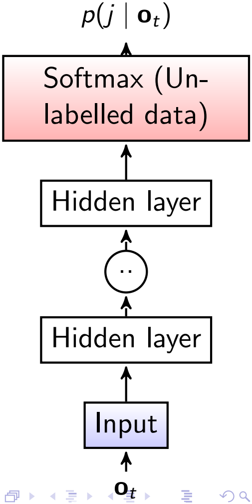

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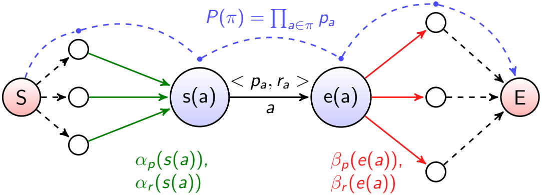

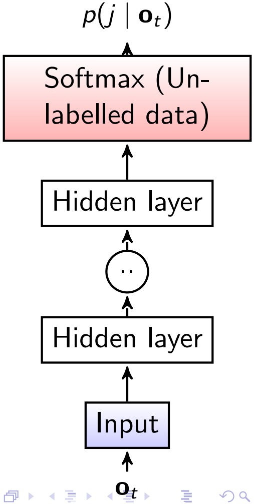

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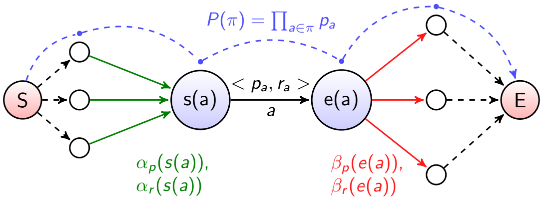

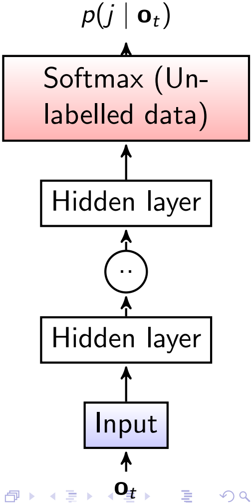

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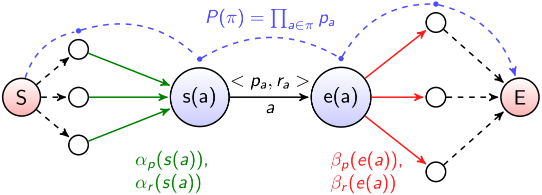

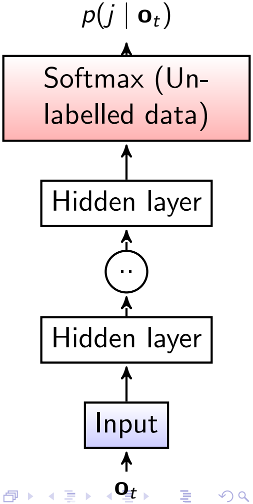

Deep Neural Network

- Multi-task architecture[2].
- Final softmax layer corresponding to unlabelled data is **discarded** at the end of every iteration.
- Scaling down gradients
- Different objective functions

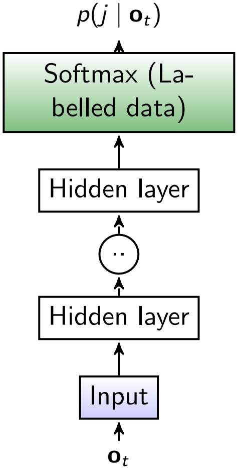

Figure: Baseline Architecture

[4]Heigold et al. [2013]

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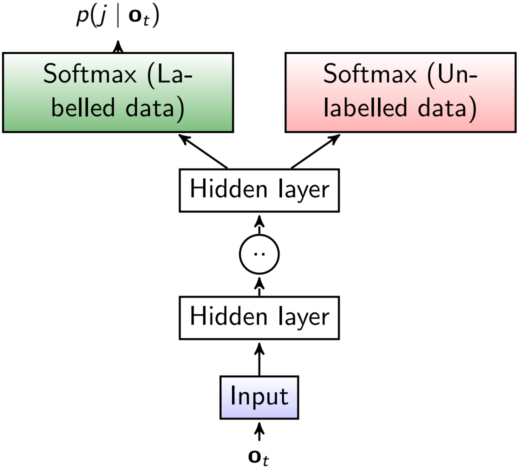

Figure: During an iteration

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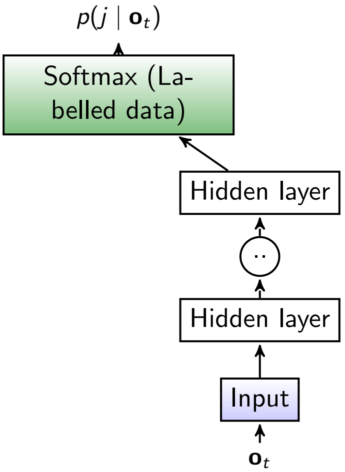

Figure: After the iteration

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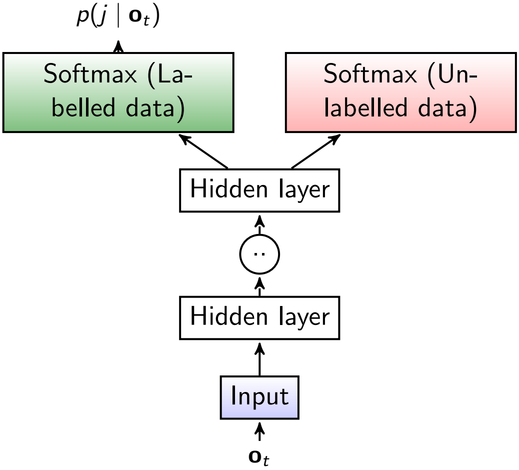

Figure: Before the next iteration

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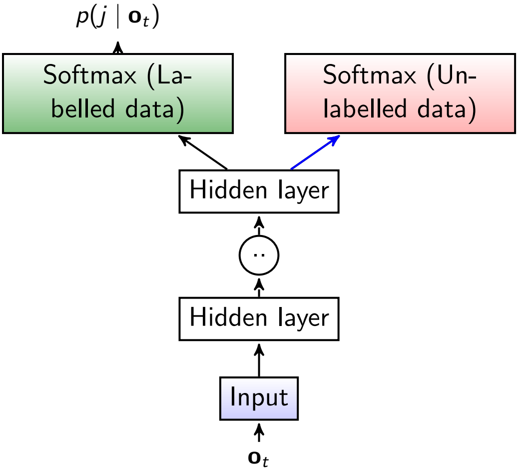

Figure: Scaling down gradients

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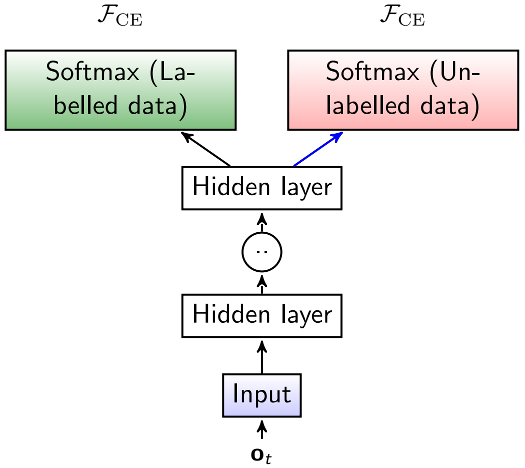

Figure: Different objectives

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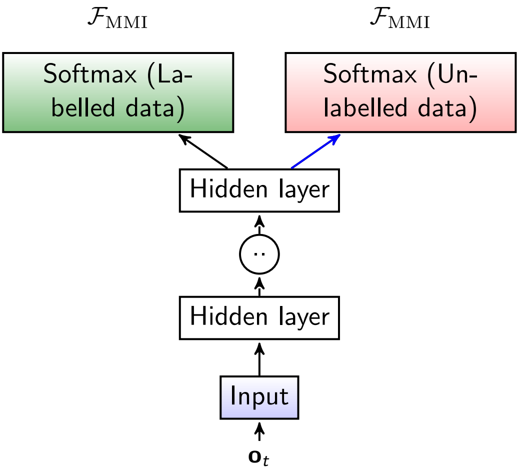

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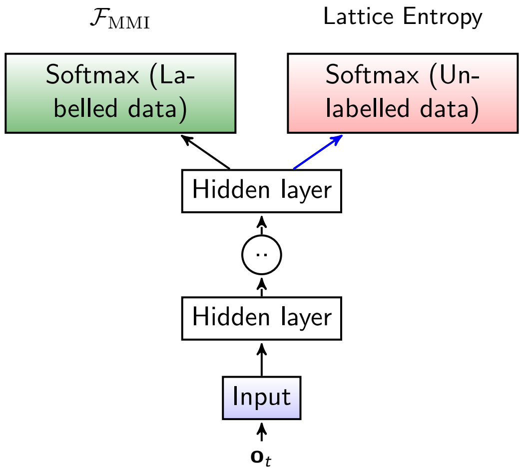

Figure: Different objectives

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Multi-task architecture - Advantages

- Reduces the tendency to learn degenerate distributions – Since lattice entropy can arbitrarily be made zero
- Force the neural network to also be good on the supervised MMI objective.

Deep Neural Network - Priors

- The DNN outputs are converted into likelihoods by dividing by a "prior" term:

$$p(\mathbf{o}_i \mid j) = \frac{p(j \mid \mathbf{o}_i)}{P(j)}$$

- The usual way of computing priors is using HMM-GMM reference alignments.
- The prior $P(j)$ is computed here by marginalizing the DNN outputs over the training data.

$$P(j) = \frac{1}{N} \sum_{i=1}^{N} p(j \mid \mathbf{o}_i).$$

- The highest change in priors is observed for the silence pdfs.

Outline

Experimental Setup

- Corpora:
  - Fisher English - 100 hours labelled data + 250 hours unlabelled
  - Babel - 4 languages in *limitedLP* condition (10 hours labelled data + 60 hours unlabelled data)
- Language model trained only on the labelled data.
- Acoustic model
  - DNN with p-norm non-linearities
  - fMLLR speaker-adapted LDA+MLLT features as input
- WER improvements also found to hold with using Time-delay neural networks (TDNN) and i-vector adaptation systems
- Tried 3-gram, 2-gram and unigram LMs for decoding unlabelled data. 3-gram gave the best performance.

Results - Fisher English

Table: *WER (%) results on Fisher English*

Type	Objective: Sup	Objective: Unsup	*dev*	*test*
Supervised training (100hr)	*CE*	-	32.0	31.2
	sMBR[3]	-	29.6	28.5
Self-training (100hr + 250hr)	*CE*	*CE*[4]	32.5	—
	sMBR	*sMBR*	—	—
Self-training in Multitask architecture	*CE*	*CE*	30.5	29.8
	sMBR	*sMBR*	29.9	28.8
Semi-supervised in Multitask architecture	*sMBR*	*Lattice Entropy*	29.4	28.1
Oracle Supervised training (350hr)	*sMBR*	-	28.5	27.5

[3] sMBR = state Minimum Bayes Risk

[4] Vesely et al. [2013]

Results - Fisher English

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Type	Objective: *Sup*	Objective: *Unsup*	*dev*	*test*
Supervised training (100hr)	*CE*	-	32.0	31.2
	sMBR[3]	-	29.6	28.5
Self-training (100hr + 250hr)	*CE*	*CE* [4]	32.5	—
	sMBR	*sMBR*	—	—
Self-training in Multitask architecture	*CE*	*CE*	30.5	29.8
	sMBR	*sMBR*	29.9	28.8
Semi-supervised in Multitask architecture	*sMBR*	*Lattice Entropy*	29.4	28.1
Oracle Supervised training (350hr)	*sMBR*	-	28.5	27.5

[3] sMBR = state Minimum Bayes Risk

[4] Vesely et al. [2013]

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[3] sMBR = state Minimum Bayes Risk
[4] Vesely et al. [2013]

Results - Babel

Table: *WER (%) results on Babel – (10hr + 60hr)*

Language	Objective		*dev2h*	*dev10h*
	Sup	*Unsup*		
Assamese	*sMBR*	-	63.9	62.2
Assamese	*sMBR*	*Lattice Entropy*	63.4	61.6
Bengali	*sMBR*	-	66.3	64.1
Bengali	*sMBR*	*Lattice Entropy*	65.8	63.8
Zulu	*sMBR*	-	65.9	67.3
Zulu	*sMBR*	*Lattice Entropy*	65.7	67.2
Tamil	*sMBR*	-	76.3	74.8
Tamil	*sMBR*	*Lattice Entropy*	76.1	74.6

Summary

- Conditional entropy is shown to be a good sequence-discriminative criterion for semi-supervised training.
- Without explicit filtering of data, the method is shown to outperform self-training methods.
- Multilingual-inspired DNN architecture used for semi-supervised training. This works better than sharing single output softmax layer.

Future work

- While we can get small gains using lattice posterior confidences, we need to work on better confidence metrics to get larger improvements in semi-supervised training.
- Use sMBR-like criterion for training on unlabelled data.
- Study the effect of amount of unlablled data versus the labelled data and the effect of the quality of the unlabelled data.

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Thank you!