Purely sequence-trained neural networks for ASR based on lattice-free MMI

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Why should you care about this ?

- It gives better WERs than the conventional way of training models.
- It's a lot faster to train
- It's a lot faster to decode

We're modifying most of the recipes in Kaldi to use this.

Doesn't always give WER improvements on small data (e.g. < 50 hours)

Connection with CTC

- This actually came out from some (unpublished) work on CTC.

- It's a simplification of an extension of an extension of CTC.

  Not really going into that work in the paper or talk. Basically I didn't see any gains with any variety of CTC (many others find this too).

- Commonalities with CTC:
  - Objective function is posterior of the correct transcript of the utterance
  - 30ms frame shift at the output

    (see at this conf., "*Lower Frame Rate NN AMs*", Pundak & Sainath)

What is it ?

- It's MMI, captain, but not as we know it.
- Normally we'd do frame-by-frame training followed by MMI.
- We train the neural net from a random start.
- The frame shift [at the neural net output] is 30ms, not 10ms.

Why is training MMI from scratch hard?

- In MMI training, in general there are two forward-backward algorithms, and we subtract the occupation counts (num-den)
  - Numerator == correct transcript
  - Denominator == all possible transcripts
- Full forward backward or even search over denominator is slow -> must be on GPU.
- On GPU, beam search is hard
  - Lose a lot of efficiency if different cores are taking different code paths or accessing different data

How do we do it?

- Full forward backward of denominator

  (on GPU, custom kernels)
- Break up utterances into fixed-size chunks

  (one-second chunks)
- Keep the denominator graph small enough

  so we can keep the forward (α) scores on the GPU for a minibatch of utterances (e.g. 128).

In next slides, will explore the consequences of these decisions.

Fixed chunk sizes

- Use 1-second chunks
  (not highly sensitive to the exact length)
- Slight overlaps or gaps where we break up utterances this way
- Append successive utterances in data preparation
  so all utterances are at least 1 second.

- *Difficulty*: how do we break up the transcripts?
  - 1-second chunks may not coincide with word boundaries.
  - ... see next slide for solution.

Numerator representation

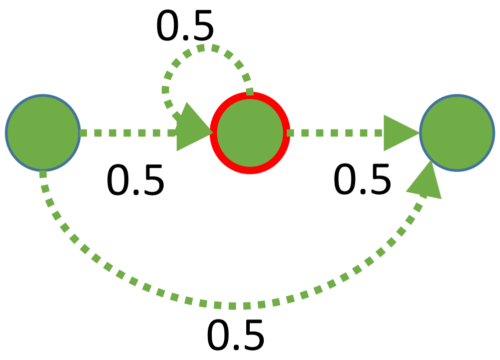
- Generate a lattice for the *numerator*, encoding alternative pronunciations of the transcript of the original utterance.
- The lattice is turned into an FST that constrains at what time the phones can appear, to +-0.05 seconds from their positions in the lattice[1].
- Process this into an FST whose labels are pdfs (neural-net outputs).
- Extract fixed-size chunks from this FST

1. In [1], FSTs are used to constrain the labels to a certain window around where the baseline system puts them. We used the same idea here.

[1] : A. Senior, H. Sak, F. de Chaumont Quitry, T. N. Sainath, and K. Rao, “Acoustic Modelling with CD-CTC-SMBR LSTM RNNS,” in *ASRU*, 2015.

Model topology and frame rate

- We use a topology that can be traversed in 1 state, and a 30ms frame shift
  - We did find that the 30ms frame shift was optimal for the 1-state topology.
- We experimented with different topologies that can be traversed in 1 state.
- Chosen topology,
  - Can generate "a", "ab", "abb", ...



Denominator graph

- Denominator graph is like a decoding graph FST (HCLG).
- Phone-level language model and no lexicon
  - so it's like HCP, where P is the phone LM.
- We construct P to minimize the size of HCP.
- It's a 4-gram, but with no backoff lower than 3-gram
  - (so that triphones not seen in training cannot be generated).
- The number of states is limited by completely removing low-count 4-gram states

  (backing off the counts to 3-gram).
- We minimize the size of the final graph

  a different-than-normal graph construction recipe

Regularization

- Very vulnerable to over-training
- Three regularization methods:
  - L2 regularization on the network *output**
  - Cross-entropy regularization
    - Add a separate cross-entropy layer that's trained but is then thrown away (that shares the hidden layers).
  - "Leaky HMM".
    - This refers to modifying the denominator-graph so that it is "stopped and restarted" with a small probability (e.g. 0.1) on each frame [like forgetting the context].

The gains from these regularization methods are somewhat additive; we use all three (and also use smaller-than-normal models).

* the outputs are in log space, they are like pseudo-likelihoods.

Frame shift issues

- In our neural nets, the input frame shift is 10ms and the output frame shift is 30ms.
- This is not quite equivalent to splicing the input, because the early TDNN and LSTM layers use frame offsets and recurrence delays that are not multiples of 30ms.
- We try to keep all such frame offsets in later layers of the network as multiples of 3 so that those layers only need to be evaluated every 3 frames.
- The neural network is obviously about 3 times faster to evaluate than for regular models (perhaps more, since model is smaller).
- In training, on each epoch we cycle through 3 differently-shifted versions of the training data (shifted by -1, 0, 1 input frame).

Speed etc.

- The parts of the computation that are specific to LF-MMI take less than 20% of the training time

  (e.g. denominator forward-backward)

- The rest is just forward-backward on the neural net.
- LF-MMI training is substantially faster than conventional cross-entropy training
  - This due to smaller neural network and faster evaluation due to frame subsampling
  - We actually see the data slightly more times (slightly fewer epochs, but we duplicate the data 3-fold on each epoch).
  - Decoding with LF-MMI models is about 2 to 3 times faster than conventional models.

Transcript Quality

- We initially found that this method did not work on AMI and TED-LIUM

  Due to lower transcript quality (vs Switchboard, Librispeech)
- The results shown in this paper for AMI are after a "fix”
  - We filtered out utterances that, after decoding with a biased LM, the lattice oracle path was still far from the transcript.
- Since publishing this paper, we've come up with a more fine-grained data cleaning method
  - Bad parts of utterances are thrown away, and good parts kept.
  - This is a completely separate process from LF-MMI training
  - ... but LF-MMI is particularly sensitive to its effect
- We now have LF-MMI "working" on TED-LIUM (done with release 2), after this data cleanup.

Left bi-phone

- All the results shown in this paper are with triphone models.
- Typically the number of leaves is about 10% to 20% fewer than the conventional DNN system (we found this worked the best).
- Since the paper was published, we've found that left biphone works *slightly* better with this type of model.
- It's also faster, of course.

Results

Comparison of regularization functions

Regularization Function			WER (%)	
Cross-entropy	Output l_2 norm	Leaky HMM	SWBD	Total
N	N	N	16.8	11.1
Y	N	N	15.9	10.5
N	Y	N	15.9	10.4
N	N	Y	16.4	10.9
Y	Y	N	15.7	10.3
Y	N	Y	15.7	10.3
N	Y	Y	15.8	10.4
Y	Y	Y	**15.6**	**10.4**

SWBD-300 Hr task : TDNN acoustic models : HUB '00 eval set

Comparison of LF-MMI and CE

Objective Function	Model (Size)	WER(%)	
		SWBD	Total
CE	TDNN-A (16.6 M)	12.5	18.2
CE→sMBR	TDNN-A (16.6 M)	11.4	16.9

SWBD-300 Hr task : TDNN acoustic models : HUB ‘00 eval set

LF-MMI with different DNNs

Model	Objective Function	WER (%)	
		SWBD	Total
TDNN	CE	12.5	18.2
	LF-MMI	10.2	15.5

15

SWBD-300 Hr task
HUB ‘00 eval set

LF-MMI in various LVCSR tasks

Standard ASR Data Set	Size	CE	CE →sMBR	LF-MMI	Rel. Δ
AMI-IHM	80 hrs	25.1%	23.8%	22.4%	6%
AMI-SDM	80 hrs	50.9%	48.9%	46.1%	6%
TED-LIUM*	118 hrs	12.1%	11.3%	11.2%	0%
Switchboard	300 hrs	18.2%	16.9%	15.5%	8%
LibriSpeech	960 hrs	4.97%	4.56%	4.28%	6%
Fisher + Switchboard	2100 hrs	15.4%	14.5%	13.3%	8%

TDNN acoustic models

Similar architecture across LVCSR tasks

Performance of lattice-free MMI

System	AM dataset	LM dataset	Hub5 2000	
			SWB	CHM
Mohd. *et al* [1]	F+S	F+S	10.6%	-
Mohd. *et al* [1]	F+S	F+S+O	9.9%	-
Mohd. *et al* [1]	F+S+O	F+S+O	9.2%	-
Saon *et al* [2]	F+S+C	F+S+O	**8.0*%**	**14.1%**
TDNN + LF-MMI	S	F+S	10.2%	20.5%
TDNN + LF-MMI → sMBR	S	F+S	10.0%	20.1%
BLSTM + LF-MMI → sMBR	S	F+S	9.6%	19.3%
TDNN + LF-MMI	F+S	F+S	9.2%	17.3%
BLSTM + LF-MMI	F+S	F+S	8.8%	15.3%

F : Fisher corpus (1800 hrs)
S: Switchboard Corpus (300 hrs)
C: Callhome corpus (14 hrs)
O: Other corpora

[1] A.R.Mohamed, F.Seide, D.Yu, J.Droppo, A.Stolcke, G.Zweig and G. Penn, "Deep bi-directional recurrent networks over spectral windows," in Proceedings of ASRU. ASRU, 2015.
[2] G. Saon, H.K. J. Kuo, S. Rennie, and M. Picheny, "The IBM 2015 English Conversational Telephone Speech Recognition System," 2015. Available: http://arxiv.org/abs/ 1505.05899

*Better results reported in Saon et. al., "*The IBM 2016 English Conversational Telephone Speech Recognition System*", this conf.

Conclusion & Future work

- Applied ideas from recent CTC efforts to MMI
  - Reduced output rate and tolerance in numerator
- Using denominator-lattice-free MMI & reduced frame rate
  - Up to 5x reduction in total training time
    - no CE pre-training, no denominator lattice generation
  - 8% rel. imp. over CE+sMBR
  - 11.5% rel. imp. over CE
- Consistent gains across several datasets (80 - 2100 hrs)

- Investigating better *data cleanup* strategies
- Examining difference in gains across feed-forward and recurrent neural networks