Context-Dependent Pre-Trained Deep Neural Networks for Large-Vocabulary Speech Recognition

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Context-Dependent Pre-Trained Deep Neural Networks for Large-Vocabulary Speech Recognition (CD-DNN-HMMs)

1. Architecture
2. Training Procedure
3. Experimental Results

Architecture

of CD-DNN-HMMs

What makes CD-DNN-HMMs special ?

- Deeper, more expressive NN architectures:
  ⟶ Unsupervised DBN pre-training algorithm.
- Use of posterior probabilities of *senones* as the output.

What is a senone ?

In a nutshell: a tied triphone state.

Transitions between words can bear more information the words themselves

→ *Triphones* or even *Quinphones*

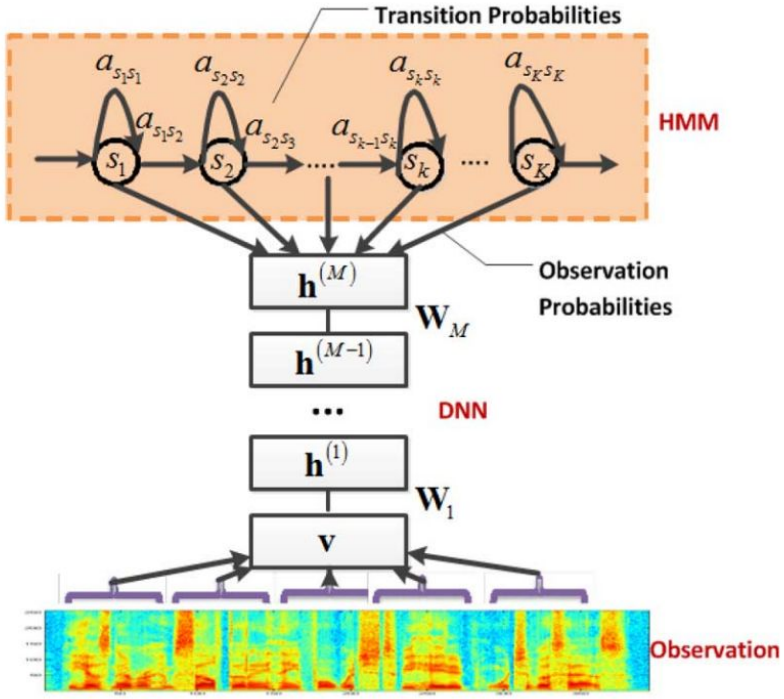
Match same range in waveform as just phones:

→ *Senone*

Prior Probability: Bayes Theorem

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

CD-DNN-HMM Illustration



Decoded Word Sequence

$$\hat{w} = \underset{w}{\operatorname{argmax}}\, p(w \mid \mathbf{x}) = \underset{w}{\operatorname{argmax}}\, p(\mathbf{x} \mid w) p(w) / p(\mathbf{x})$$

Training Procedure

For CD-DNN-HMMs

Algorithmic Main Steps

1. Convert CD-GMM-HMM to CD-DNN-HMM
2. Convert triphone states
3. Pre-Training & state-level alignment
4. Fine-tuning and re-estimating transition probabilities
5. End or iterate

Step 1: Convert CD-GMM-HMM to CD-DNN-HMM

Train a best tied-state CD-GMM-HMM system where state tying is determined based on the data-driven decision tree. Denote the CD-GMM-HMM: *gmm-hmm*.

Parse gmm-hmm and:

1. Give each senone name an ordered *senoneid* starting from 0 (training label for DNN fine-tuning).
2. Generate a mapping from each physical tri-phone state to the corresponding senoneid. Denote this mapping *state2id*.

Step 2: Convert triphone states

Convert gmm-hmm to the corresponding CD-DNN-HMM *dnn–hmm1* by borrowing the tri-phone and senone structure as well as the transition probabilities from *gmm-hmm*.

Step 3: Pre-Training & state-level alignment

Pre-train each layer in the DNN bottom-up layer by layer and call the result: *ptdnn*.

Use *gmm-hmm* to generate state-level alignment: *align-raw*. the training set.

Step 4: Fine-tuning and re-estimating transition probabilities

Convert *align-raw* to *align* where each physical tri-phone state is converted to *senoneid*, then fine-tune the DBN starting from *ptdnn*.

Denote the DBN: *dnn*.

Re-estimate the transition probabilities using dnn and *dnn-hmm1* to maximize the likelihood of observing the features. Denote the new CD-DNN-HMM: *dnn-hmm2*.

Step 5: End or iterate

Exit if no recognition accuracy improvement is observed in the development set; Otherwise use *dnn* and *dnn-hmm2* to generate a new state-level alignment *align-raw* on the training set and go to step 4.

Algorithmic Main Steps: Recap

1. Convert CD-GMM-HMM to CD-DNN-HMM
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5. End or iterate

Experimental Results

On CD-GMM-HMMs/ CD-DNN-HMMs

Dataset Description

Bing Mobile voice search application (2008).

Examples of queries:

- “Mc-Donalds”, “Denny’s restaurant”, “oak ridge church.”

Dataset Description (2)

INFORMATION ON THE BUSINESS SEARCH DATASET

	Hours	Number of Utterances
Training Set	24	32,057
Development Set	6.5	8,777
Test Set	9.5	12,758

CD-GMM-HMM Baseline Systems

- Maximum-likelihood (ML)
- Maximum mutual information (MMI)
- Minimum phone error (MPE) criteria

CD-GMM-HMM BASELINE RESULTS

Criterion	Dev Accuracy	Test Accuracy
ML	62.9%	60.4%
MMI	65.1%	62.8%
MPE	65.5%	63.8%

CD-DNN-HMM (Context dependency)

COMPARISON OF CONTEXT-INDEPENDENT MONOPHONE STATE LABELS AND CONTEXT-DEPENDENT TRIPHONE SENONE LABELS

# Hidden Layers	# Hidden Units	Label Type	Dev Accuracy
1	2K	Monophone States	59.3%
1	2K	Triphone Senones	68.1%
3	2K	Monophone States	64.2%
3	2K	Triphone Senones	69.6%

CD-DNN-HMM (Pre-training)

CONTEXT-DEPENDENT MODELS WITH AND WITHOUT PRE-TRAINING

Model Type	# Hidden Layers	# Hidden Units	Dev Accuracy
without pre-training	1	2K	68.0%
without pre-training	2	2K	68.2%
with pre-training	1	2K	68.1%
with pre-training	2	2K	69.5%

CD-DNN-HMM (Hidden Layers)

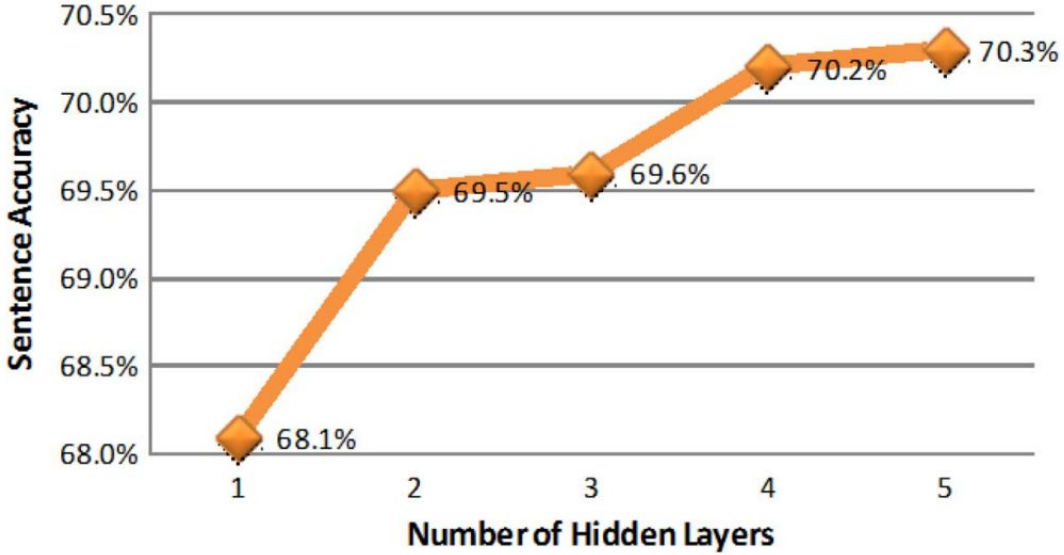

Fig. 2. Relationship between the recognition accuracy and the number of layers. Context-dependent models with 2 K hidden units per layer were used to obtain the results.

CD-DNN-HMM (Hidden Layers)

SUMMARY OF TRAINING TIME USING 24 HOURS OF TRAINING DATA AND 2 K HIDDEN UNITS PER LAYER

Type	# of Layers	Time Per Epoch	# of Epochs
Pre-train	1	0.2 h	50
Pre-train	2	0.5 h	20
Pre-train	3	0.6 h	20
Pre-train	4	0.7 h	20
Pre-train	5	0.8 h	20
Fine-tune	4	1.2 h	12
Fine-tune	5	1.4 h	12

5 layers:
Training → 62 hours
Fine-Tuning → 16.8 hours

CD-DNN-HMM (Decoding Time)

Dell Precision T3500 workstation:

- Quad core
- CPU clock speed: 2.66 GHz
- 8 MB of L3 CPU cache
- 12 GB of 1066 MHz DDR3 SDRAM

CD-DNN-HMM (Decoding Time) (2)

SUMMARY OF DECODING TIME

Processing Unit	# of Layers	DNN Time Per Frame	Search Time Per Frame	Real-time Factor
CPU	4	4.3 ms	1.5 ms	0.58
GPU	4	0.16 ms	1.5 ms	0.17
CPU	5	5.2 ms	1.5 ms	0.67
GPU	5	0.20 ms	1.5 ms	0.17

CD-DNN-HMM (Decoding Time) (2)

- Total time to train the system from scratch is about four days.
- Using a GPU speeds up training by about a factor of 30 faster than just using the CPU.
- Without using a GPU, it would take about three months to train the best system.

CD-DNN-HMM (Bottleneck)

Bottleneck: mini-batch stochastic gradient descend (SGD) algorithm used to train the DNNs:

- Inherently sequential
- Difficult to parallelize across machines.

So far SGD with a GPU is the best training strategy for CD-DNN-HMMs.

→ GPU can exploit the parallelism in the layered DNN structure.

Conclusion

Conclusion

- Training is considerably more expensive than for CD-GMM-HMM systems
- Decoding is still very efficient
- In theory, CD-DNN-HMM training is quite scalable
- In practice, it is quite challenging to train on tens of thousands of hours of data.

→ Finding new ways to parallelize training may require a better theoretical understanding of deep learning