Who Can Understand Your Speech Better -- Deep Neural Network or Gaussian Mixture Model?

Dong Yu

Microsoft Research

Thanks to my collaborators:

Li Deng, Frank Seide, Gang Li, Mike Seltzer, Jinyu Li, Jui-Ting Huang, Kaisheng Yao, Adam Eversole, George Dahl, Abdel-rahman Mohamed, Xie Chen, Hang Su, Ossama Abdel-Hamid, Eric Wang, Andrew Maas, and many more

Demo: Real Time Speech to Speech Translation

http://youtu.be/Nu-nlQqFCKg

Microsoft Chief Research Officer Dr. Rick Rashid demoed the real time speech-to-speech translation technique at 14th Computing in the 21st Century Conference held at Tianjin, China, on Oct. 25, 2012.

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Speech to Speech Translation

Speech Recognition

Frank Seide
Gang Li
Dong Yu
Li Deng

Machine Translation

Xiaodong He
Dongdong Zhang
Mei-Yuh Hwang
Mu Li
Mohamed Abdel-Hady
Ming Zhou

Personalized Speech Synthesis

Yao Qian
Frank Soong
Lijuan Wang

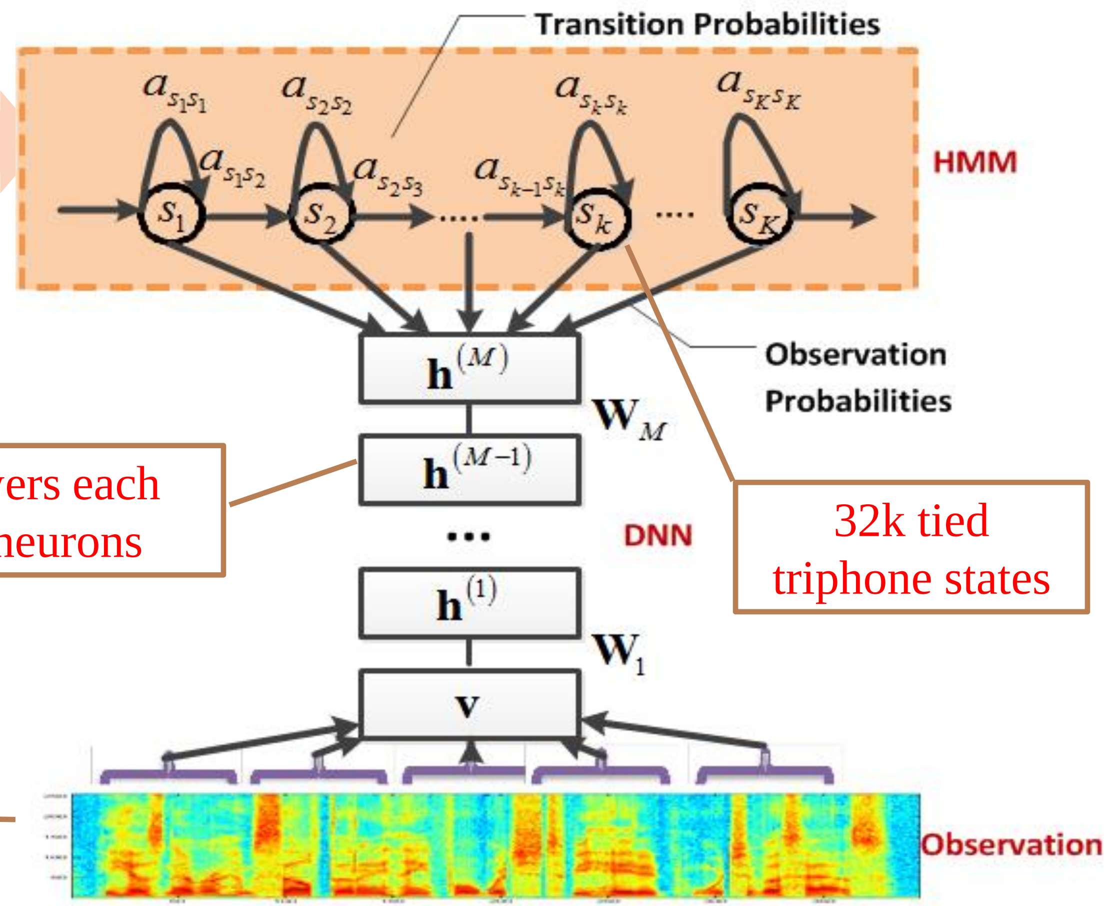
Project Management: Noelle Sophy, Chris Wendt

Speech to Speech Translation

Speech Recognition

SI DNN trained with 2000-hr SWB data

Has 180 million parameters



7 hidden layers each with 2048 neurons

32k tied triphone states

11 frames of 52-dim plp feature

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DNN-HMM Performs Very Well

(Dahl, Yu, Deng, Acero 2012, Seide, Li, Yu 2011, Chen et al. 2012)

- **Table:** Voice Search SER (24 hours training)

AM	Setup	Test
GMM-HMM	MPE (760 24-mixture)	36.2%
DNN-HMM	5 layers x 2048	30.1% (-17%)

- **Table:** Switch Board WER (309 hours training)

AM	Setup	Hub5'00-SWB	RT03S-FSH
GMM-HMM	BMMI (9K 40-mixture)	23.6%	27.4%
DNN-HMM	7 x 2048	15.8% (-33%)	18.5% (-33%)

- **Table:** Switch Board WER (2000 hours training)

AM	Setup	Hub5'00-SWB	RT03S-FSH
GMM-HMM (A)	BMMI (18K 72-mixture)	21.7%	23.0%
GMM-HMM (B)	BMMI + fMPE	19.6%	20.5%
DNN-HMM	7 x 3076	14.4% (A: -34% B: -27%)	15.6% (A: -32% B: -24%)

DNN-HMM Performs Very Well

- **Microsoft** audio video indexing service (Knies, 2012)
  - "It's a big deal. The benefits, says Behrooz Chitsaz, director of Intellectual Property Strategy for Microsoft Research, are improved accuracy and faster processor timing. He says that tests have demonstrated that the algorithm provides a 10- to 20-percent relative error reduction and uses about 30 percent less processing time than the best-of-breed speech-recognition algorithms based on so-called Gaussian Mixture Models."
- **Google** voice search (Simonite, 2012):
  - "Google is now using these neural networks to recognize speech more accurately, a technology increasingly important to Google's smartphone operating system, Android, as well as the search app it makes available for Apple devices (see "Google's Answer to Siri Thinks Ahead"). "We got between 20 and 25 percent improvement in terms of words that are wrong," says Vincent Vanhoucke, a leader of Google's speech-recognition efforts. "That means that many more people will have a perfect experience without errors."

Outline

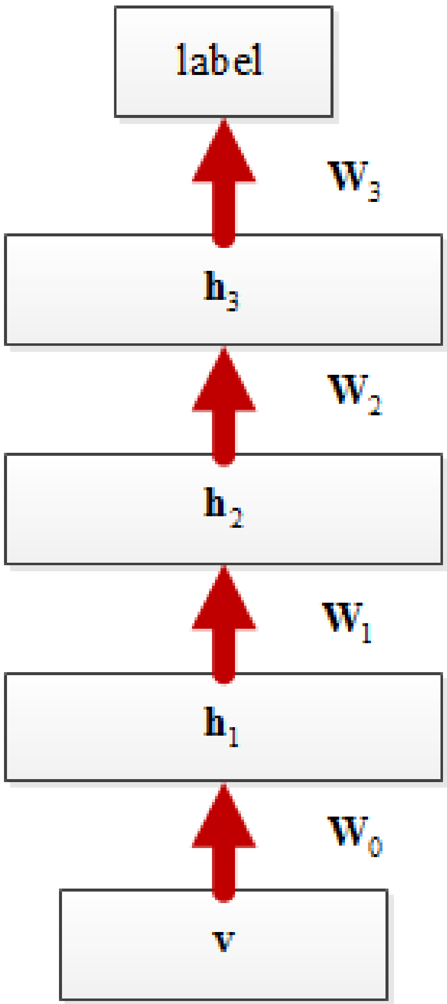
- **CD-DNN-HMM**
- Invariant Features
- Once Considered Obstacles
- Other Advances
- Summary

Deep Neural Network

- A fancy name for multi-layer perceptron (MLP) with many hidden layers.
- Each sigmoidal hidden neuron follows Bernoulli distribution
- The last layer (softmax layer) follows multinomial distribution

$$\mathrm{p}(l = k|\mathbf{h}; \theta) = \frac{exp\left(\sum_{i=1}^{H} \lambda_{ik} h_i + a_k\right)}{Z(\boldsymbol{h})}$$

- Training can be difficult and tricky. Optimization algorithm and strategy can be important.



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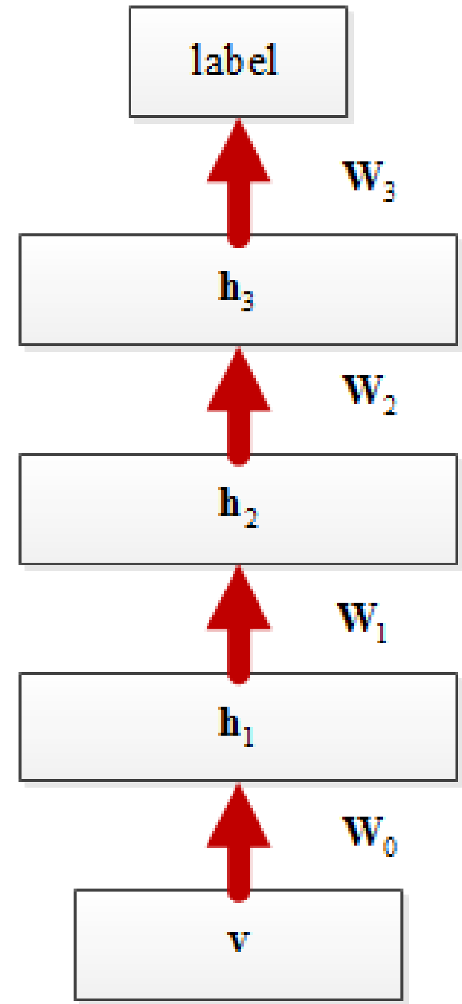
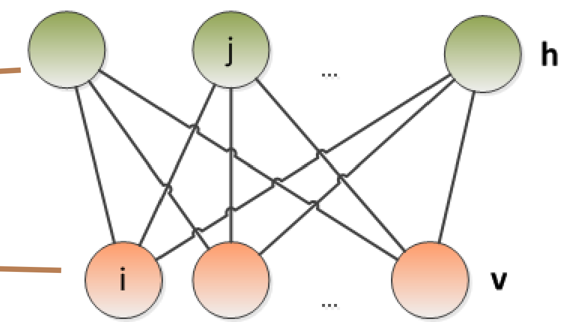


Restricted Boltzmann Machine

(Hinton, Osindero, Teh 2006)

Hidden Layer
No within layer connection

Visible Layer
No within layer connection



- Joint distribution $\mathrm{p}(\mathbf{v},\mathbf{h};\theta)$ is defined in terms of an energy function $\mathrm{E}(\mathbf{v},\mathbf{h};\theta)$

$$\mathrm{p}(\mathbf{v},\mathbf{h};\theta)=\frac{exp\left(-\mathrm{E}(\mathbf{v},\mathbf{h};\theta)\right)}{Z}$$

$$\mathrm{p}(\mathbf{v};\theta)=\sum_{\mathbf{h}}\frac{exp\left(-\mathrm{E}(\mathbf{v},\mathbf{h};\theta)\right)}{Z}=\frac{exp\left(-\mathrm{F}(\boldsymbol{v};\theta)\right)}{Z}$$

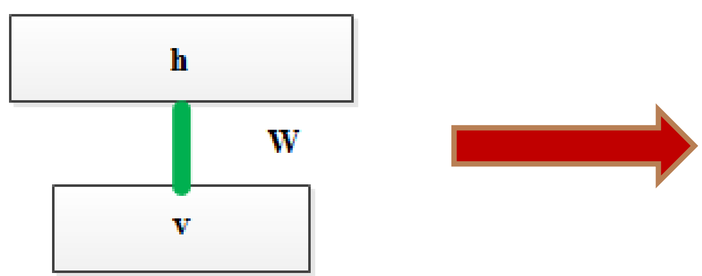
- Conditional independence

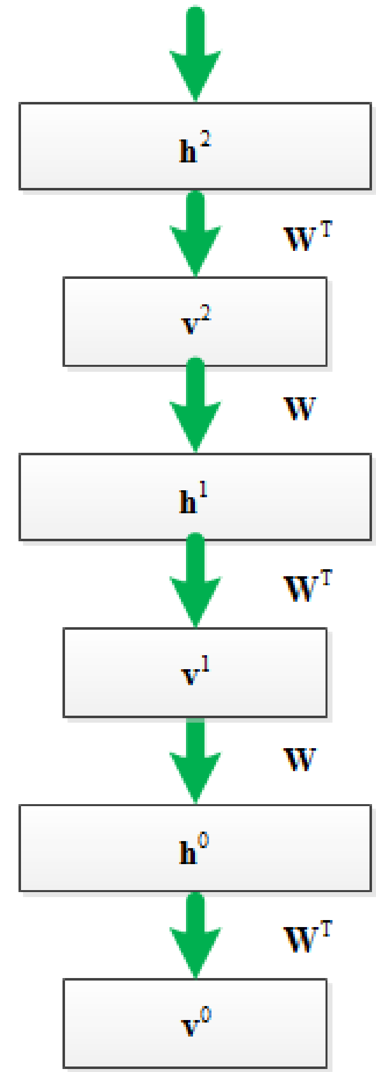
$$p(\mathbf{h}|\mathbf{v})=\prod_{\mathrm{j}=0}^{H-1}p(h_j|\mathbf{v})$$

$$p(\mathbf{v}|\mathbf{h})=\prod_{\mathrm{i}=0}^{V-1}p(v_i|\mathbf{h})$$

Generative Pretraining a DNN

- First learn with all the weights tied
  - equivalent to learning an RBM
- Then freeze the first layer of weights and learn the remaining weights (still tied together).
  - equivalent to learning another RBM, using the aggregated conditional probability on $\boldsymbol{h}_0$ as the data
  - Continue the process to train the next layer
- Intuitively $\log p(\boldsymbol{v})$ improves as new layer is added and trained.





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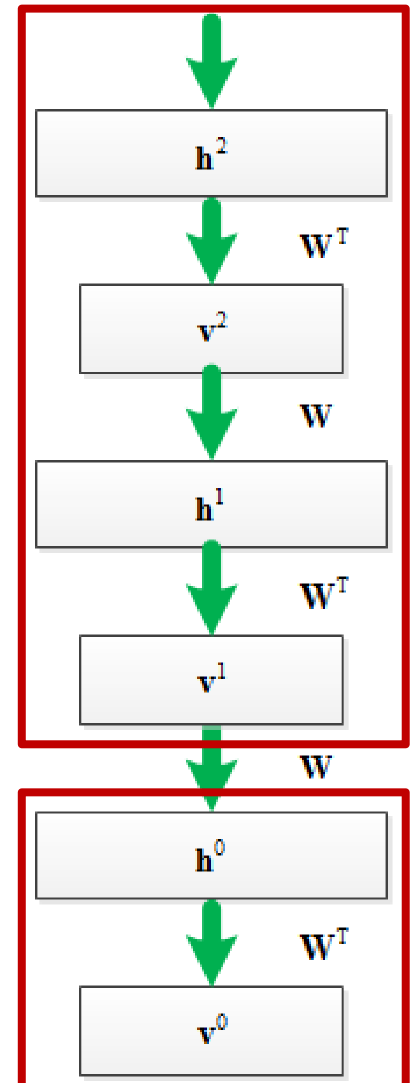

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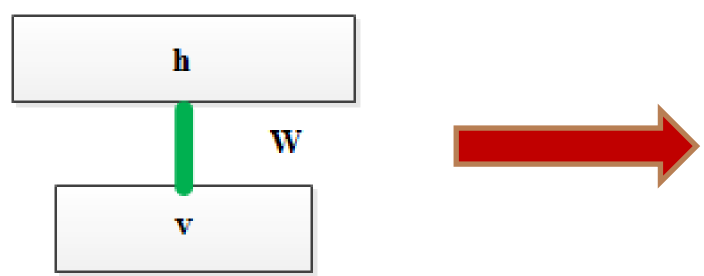

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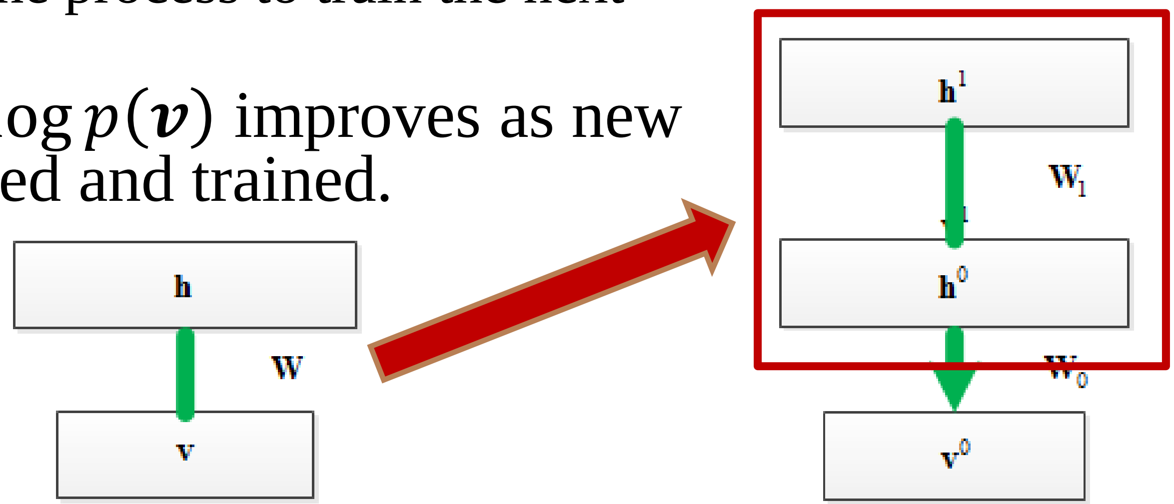

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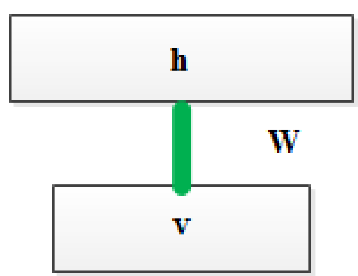
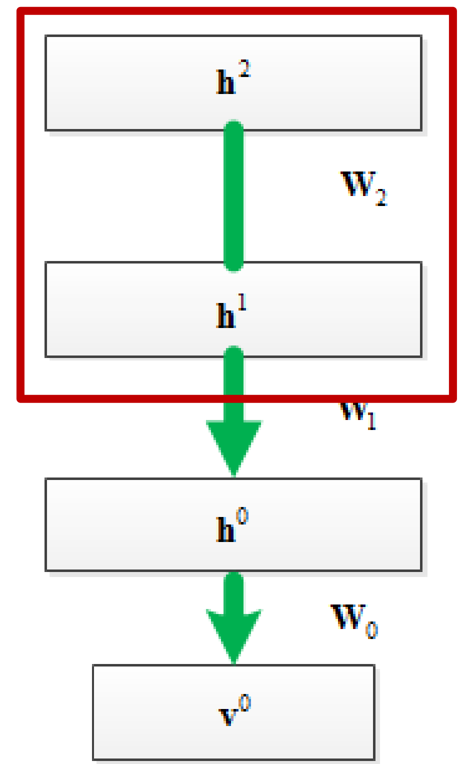
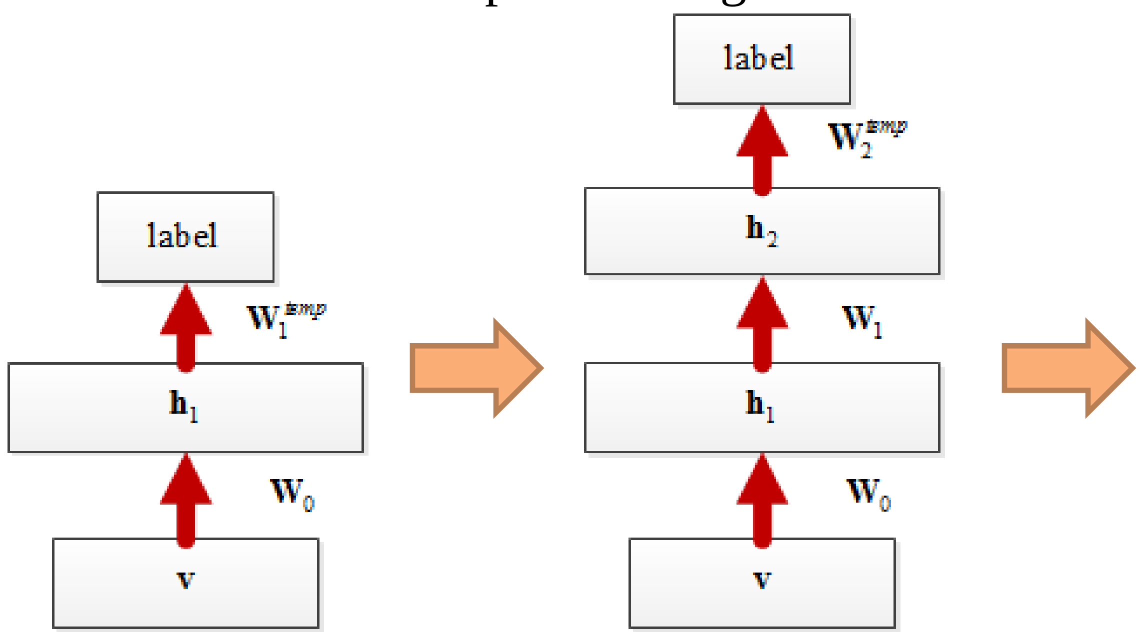
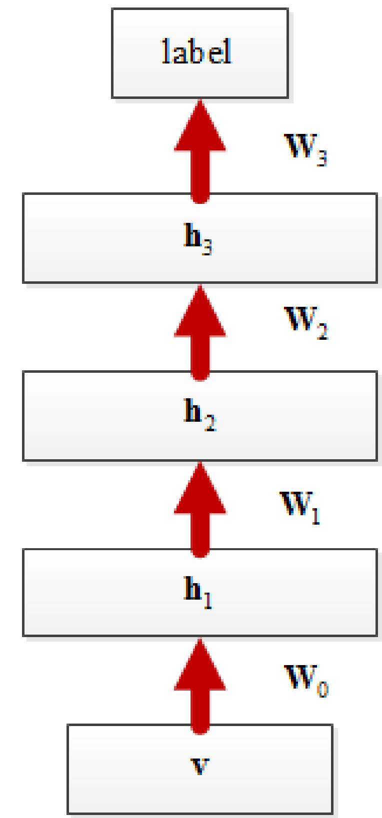




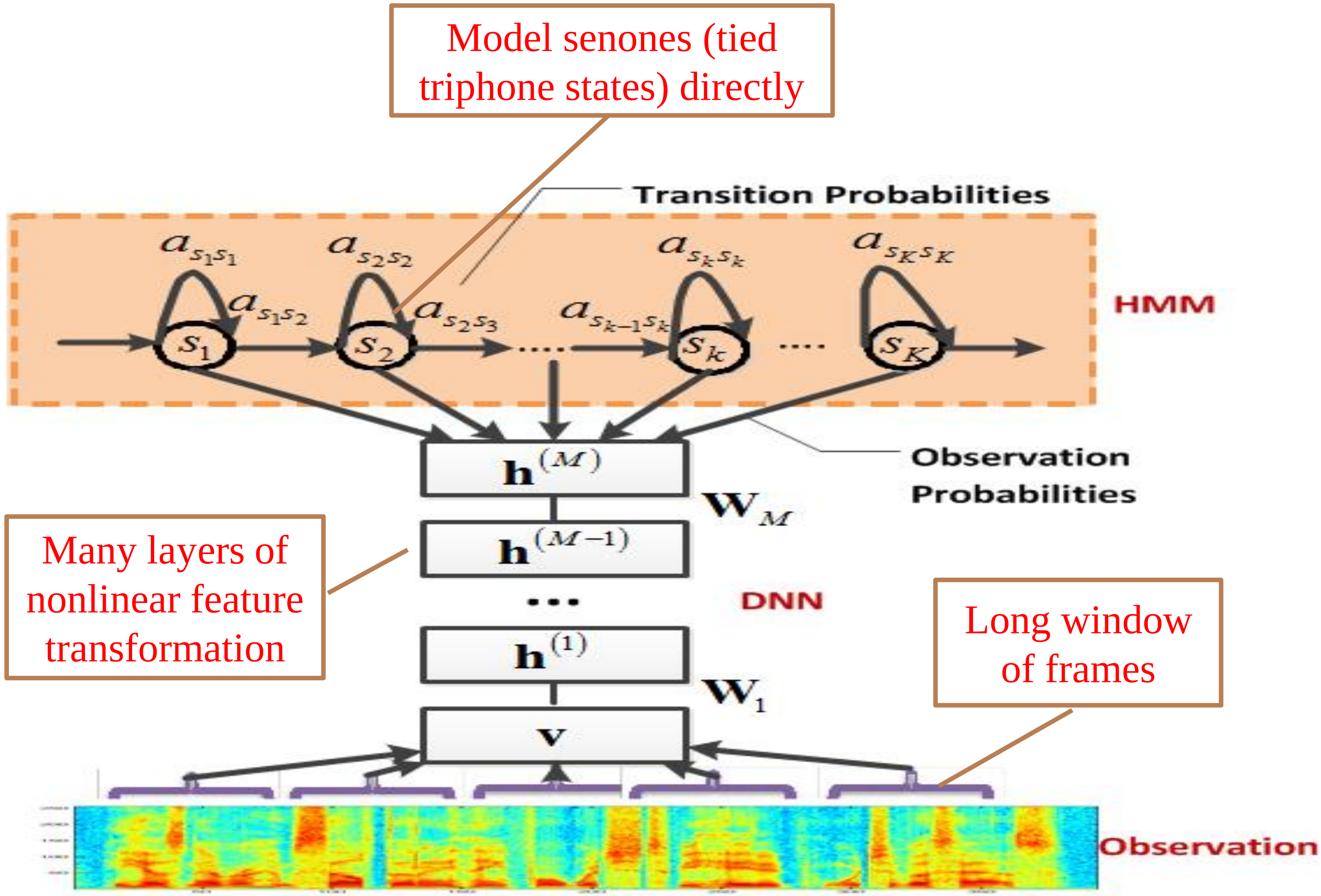
Discriminative Pretraining

- Train a single hidden layer DNN using BP (without convergence)
- Insert a new hidden layer and train it using BP (without convergence)
- Do the same thing till the predefined number of layers is reached
- Jointly fine-tune all layers till convergence
- Can reduce gradient diffusion problem
- Guaranteed to help if done right





CD-DNN-HMM: Three Key Components
(Dahl, Yu, Deng, Acero 2012)



Modeling Senones is Critical

- **Table:** 24-hr Voice Search (760 24-mixture senones)

Model	monophone	senone
GMM-HMM MPE	-	36.2
DNN-HMM 1× 2K	41.7	31.9
DNN-HMM 3 ×2k	35.8	30.4

- **Table:** 309-hr SWB (9k 40-mixture senones)

Model	monophone	senone
GMM-HMM BMMI	-	23.6
DNN-HMM 7× 2K	34.9	17.1

- ML-trained CD-GMM-HMM generated alignment was used to generate senone and monophone labels for training DNNs.

Exploiting Neighbor Frames

- **Table:** 309-hr SWB (GMM-HMM BMMI = 23.6%)

Model	1 frame	11 frames
CD-DNN-HMM 1× **4634**	26.0	22.4
CD-DNN-HMM 7 ×2k	23.2	17.1

ML-trained CD-GMM-HMM generated alignment was used to generate senone labels for training DNNs

- It seems 23.2% is only slightly better than 23.6% but note that DNN is not trained using sequential criterion but GMM is.
- To exploit info in neighbor frames, GMM systems need to use fMPE, region dependent transformation, or tandem structure

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Deeper Model is More Powerful

(Seide, Li, Yu 2011, Seide, Li, Chen, Yu 2011)

- **Table:** 309-hr SWB (GMM-HMM BMMI = 23.6%)

L×N	DBN-Pretrain	1×N	DBN-Pretrain
1×2k	24.2	1×2k	24.2
2×2k	20.4	-	-
3×2k	18.4	-	-
4 ×2k	17.8	-	-
5×2k	17.2	1×3772	22.5
7 ×2k	17.1	1×4634	22.6
9×2k	17.0	-	-
9× 1k	17.9	-	-
5×3k	17.0	-	-
		1× 16k	22.1

Pretraining Helps but Not Critical

(Seide, Li, Yu 2011, Seide, Li, Chen, Yu 2011)

L×N	DBN-Pretrain	BP	LBP	Discriminative Pretrain
1×2k	24.2	24.3	24.3	24.1
2×2k	20.4	22.2	20.7	20.4
3×2k	18.4	20.0	18.9	18.6
4 ×2k	17.8	18.7	17.8	17.8
5×2k	17.2	18.2	17.4	17.1
7 ×2k	17.1	17.4	17.4	16.8
9×2k	17.0	16.9	16.9	-
9× 1k	17.9	-	-	-
5×3k	17.0	-	-	-

- Stochastic gradient alleviates the optimization problem.
- Large amount of training data alleviates the overfitting problem.
- Pretraining helps to make BP more robust

Outline

- CD-DNN-HMM
- **Invariant Features**
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DNN Is Powerful and Efficient

- The desirable model should be powerful and efficient to represent complex structures
  - DNN can model any mapping (powerful): universal approximator -> same as shallow model
  - DNN is efficient in representation: need fewer computational units for the same function by sharing lower-layer results -> better than shallow models
- **DNN learns invariant and discriminative features**

What Makes ASR Difficult?

Variability, Variability, Variability

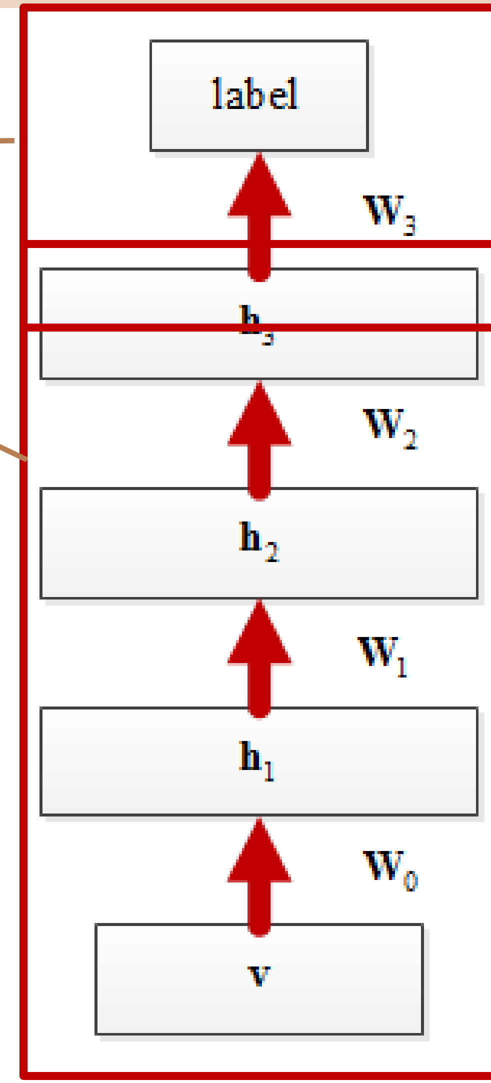
Speaker	Environment	Device
• Accents • Dialect • Style • Emotion • Coarticulation • Reduction • Pronunciation • Hesitation • …	• Noise • Side talk • Reverberation • …	• Head phone • Land phone • Speaker phone • Cell phone • …

Interactions between these factors are complicated and nonlinear

DNN Learns Invariant and Discriminative Features

Log-linear classifier

Many layers of nonlinear feature transformation



- Joint feature learning and classifier design
  - Bottleneck or tandem feature does not have this property
- Many simple non-linearities = One complicated non-linearity
- Features at higher layers are more invariant and discriminative than those at lower layers

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Higher Layer Features More Invariant

$$\left\|\delta^{l+1}\right\| = \left\|\sigma\left(z^l\left(v^l+\delta^l\right)\right) - \sigma\left(z^l\left(v^l\right)\right)\right\| \cong \left\|diag\left(\sigma'\left(z^l\left(v^l(t)\right)\right)\right)\left(\left(w^l\right)^T \delta^l\right)\right\| \leq \boxed{\left\|diag\left(\sigma'\left(z^l\left(v^l(t)\right)\right)\right)\left(w^l\right)^T\right\|}\left\|\delta^l\right\|$$

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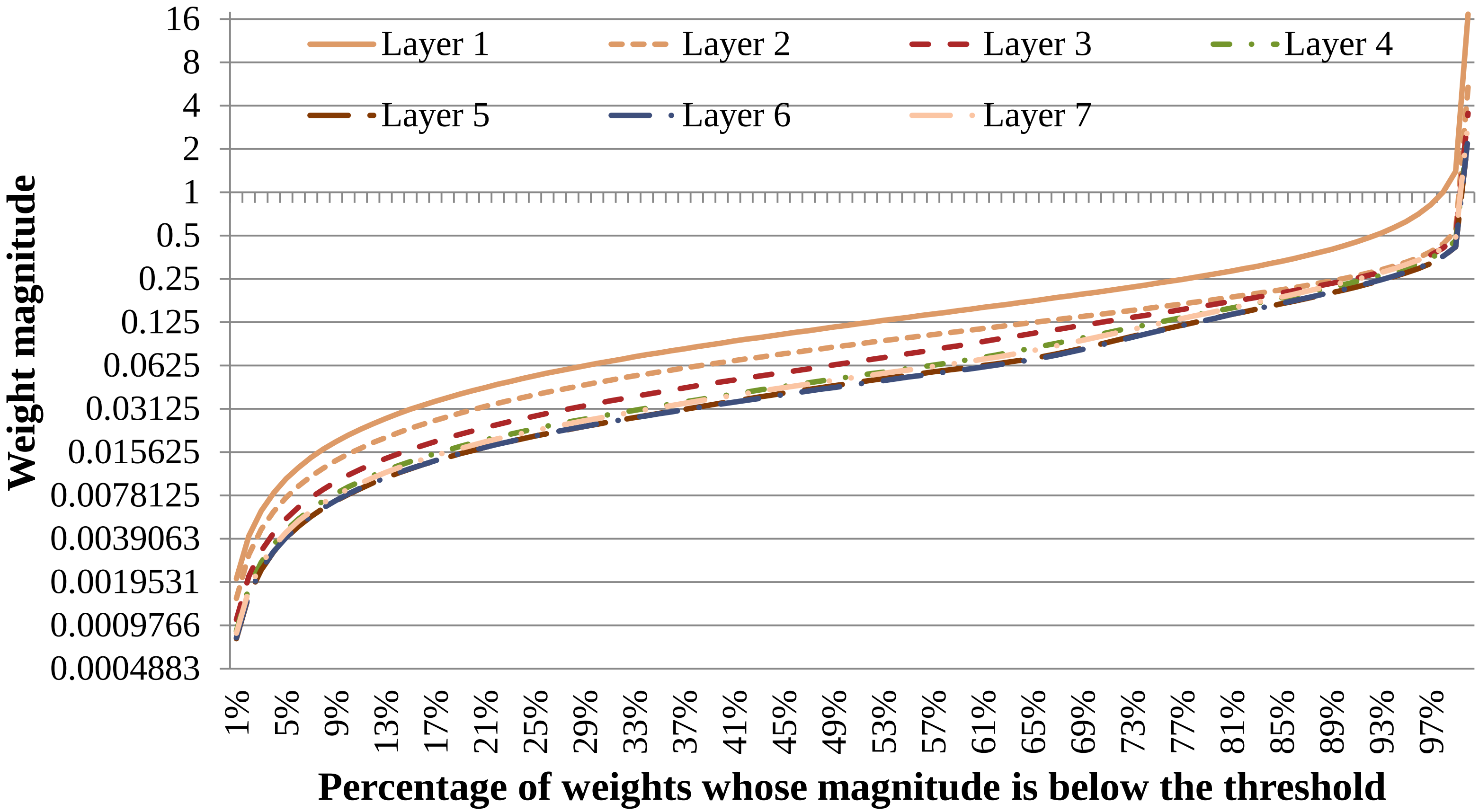

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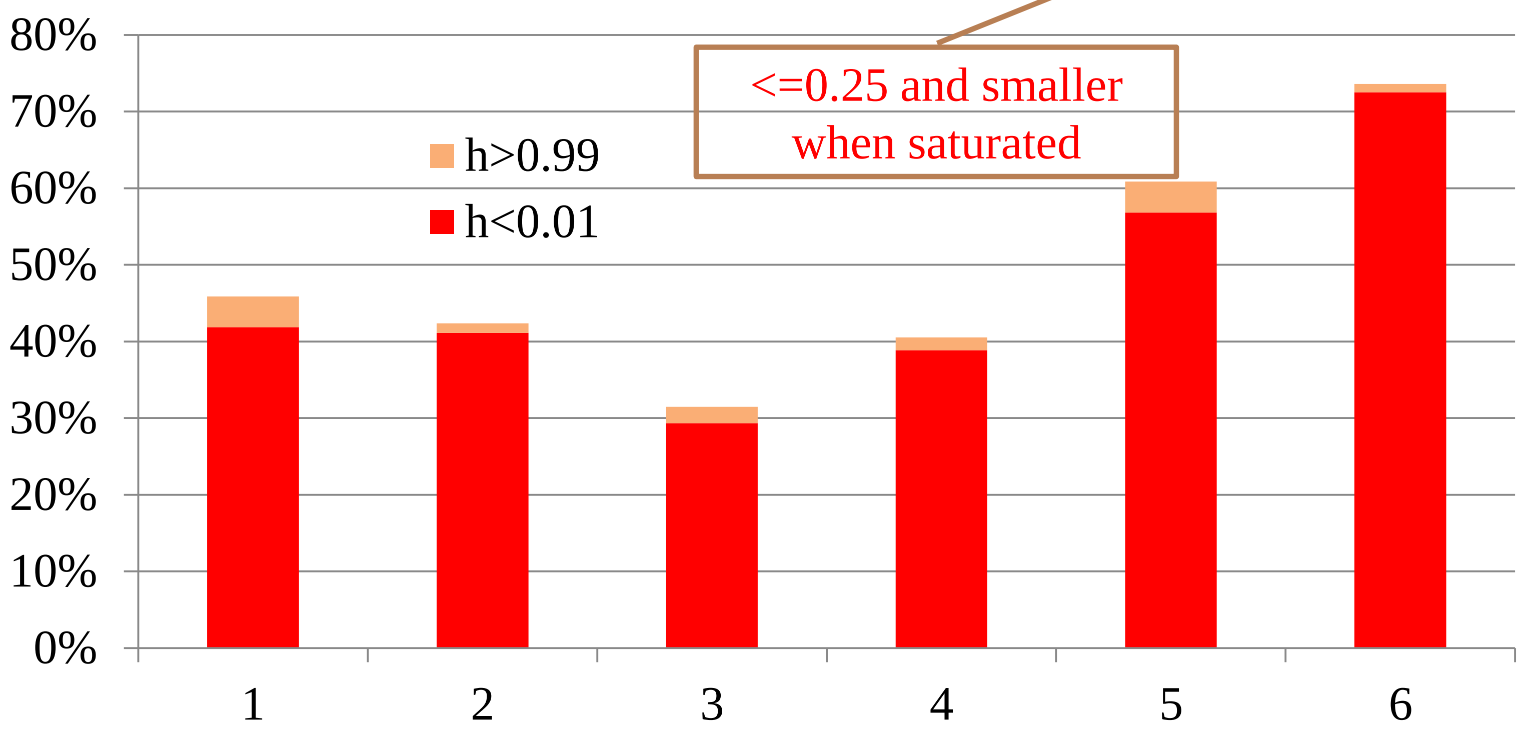
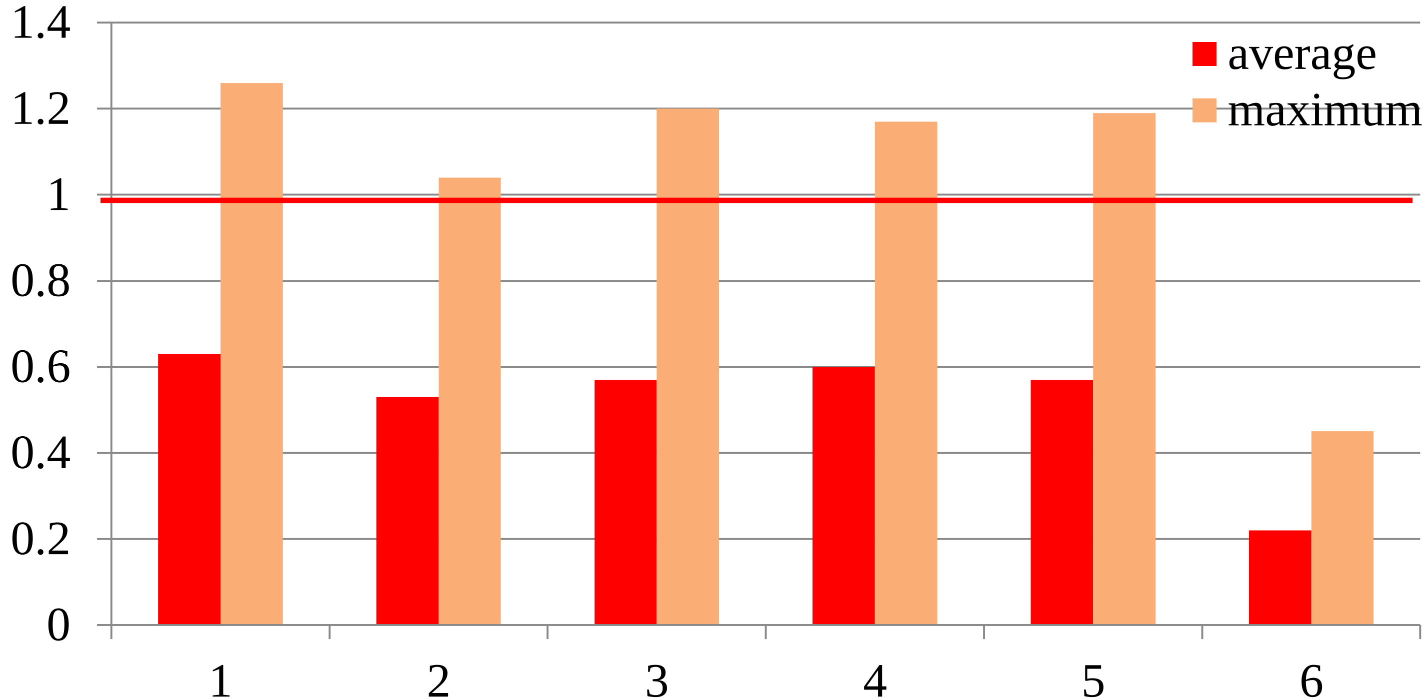


- Percentage of saturated hidden units.
- H<0.01 are inactive neurons. Higher layers are more sparse

Higher Layer Features More Invariant

$$\left\|\delta^{l+1}\right\| = \left\|\sigma\left(z^l\left(v^l+\delta^l\right)\right) - \sigma\left(z^l\left(v^l\right)\right)\right\| \cong \left\|diag\left(\sigma'\left(z^l\left(v^l(t)\right)\right)\right)\left(\left(w^l\right)^T\delta^l\right)\right\| \le \boxed{\left\|diag\left(\sigma'\left(z^l\left(v^l(t)\right)\right)\right)\left(w^l\right)^T\right\|}\left\|\delta^l\right\|$$



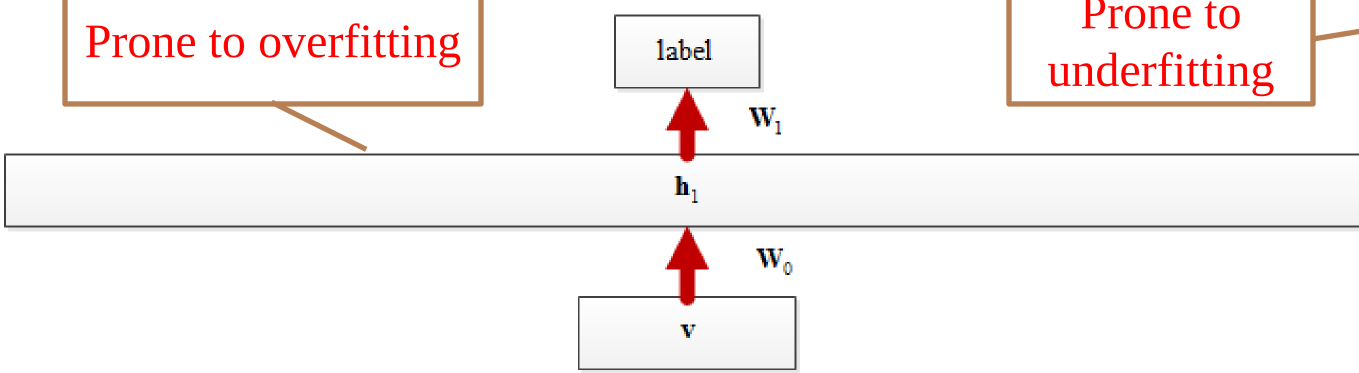
$$\left\|diag\left(\sigma'\left(z^l\left(v^l(t)\right)\right)\right)\left(w^l\right)^T\right\|$$

If the norm <1 the variation shrinks one layer higher

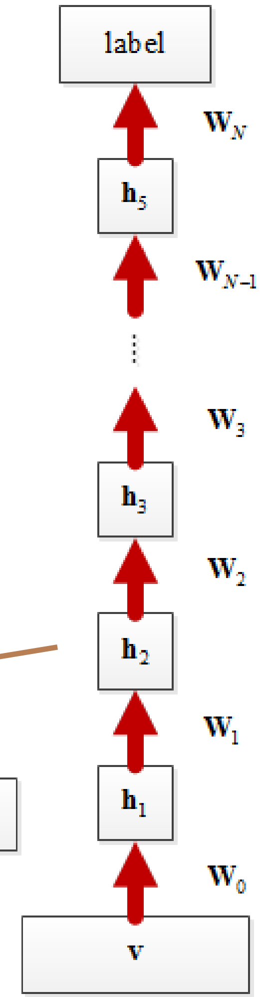
Balance Overfitting and Underfitting

- Achieved by adjusting width and depth -> shallow model is lack of depth adjustment
- DNN adds constrains to the space of transformations – less likely to overfit
- Larger variability -> wider layers
- Small training set -> narrower layers
- A good system is deep and wide.

Prone to overfitting



Prone to underfitting



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Decoding Speed

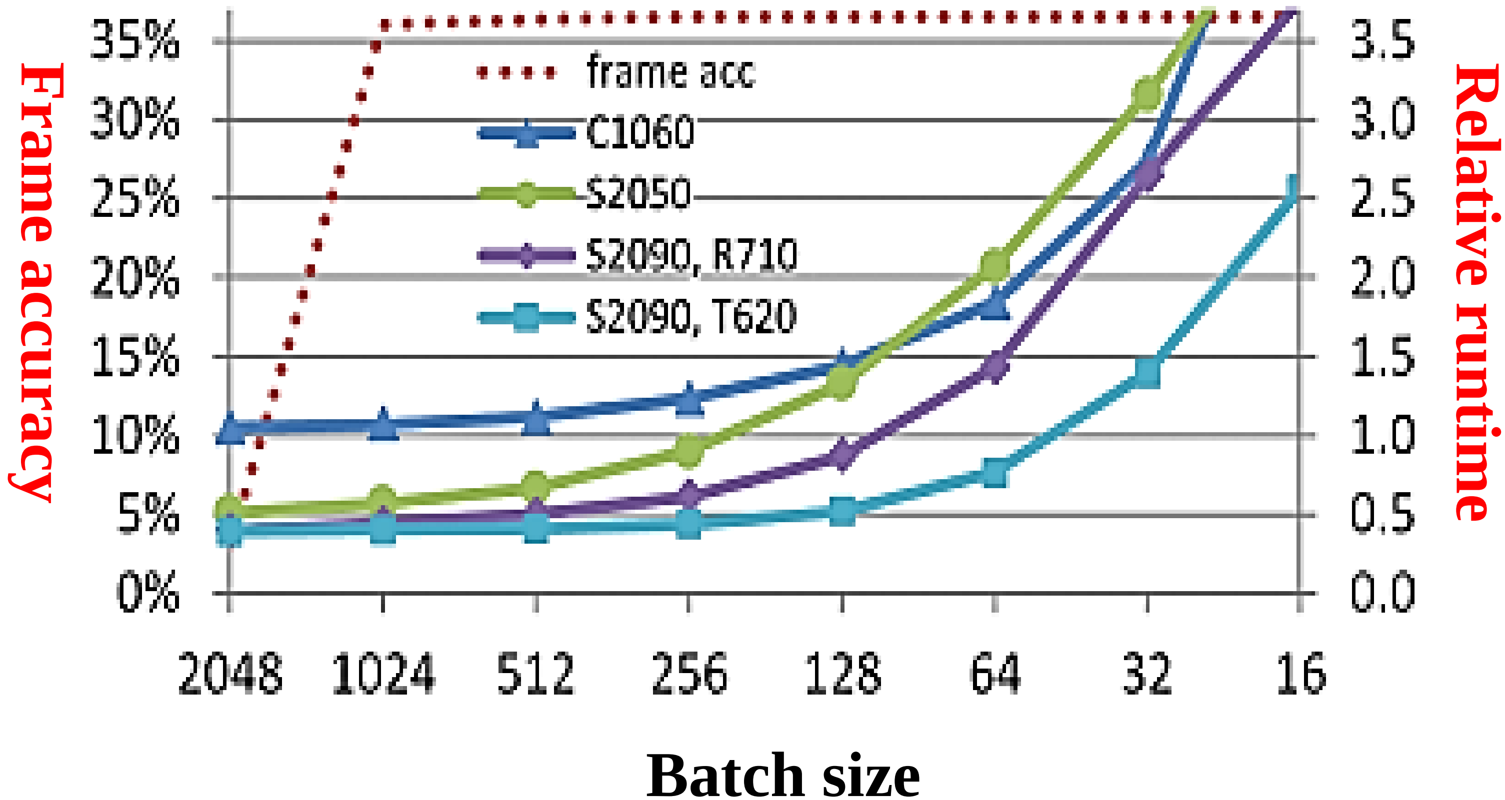
(Senior et al. 2011)

- Well within real time with careful engineering
- Setup: (1) DNN: 440:2000X5:7969 (2) single CPU (4) GPU NVIDIA Tesla C2070

Technique	Real time factor	Note
Floating-point baseline	3.89	
Floating-point SSE2	1.36	4-way parallel (16 bytes)
8-bit quantization	1.52	Hidden: unsigned char, weight: signed char
Integer SSSE3	0.51	16-way parallel
Integer SSE4	0.47	Faster 16-32 conversion
Batching	0.36	batches over tens of ms
Lazy evaluation	0.26	Assume 30% active senone
Batched lazy evaluation	**0.21**	Combine both

Training (Single GPU)

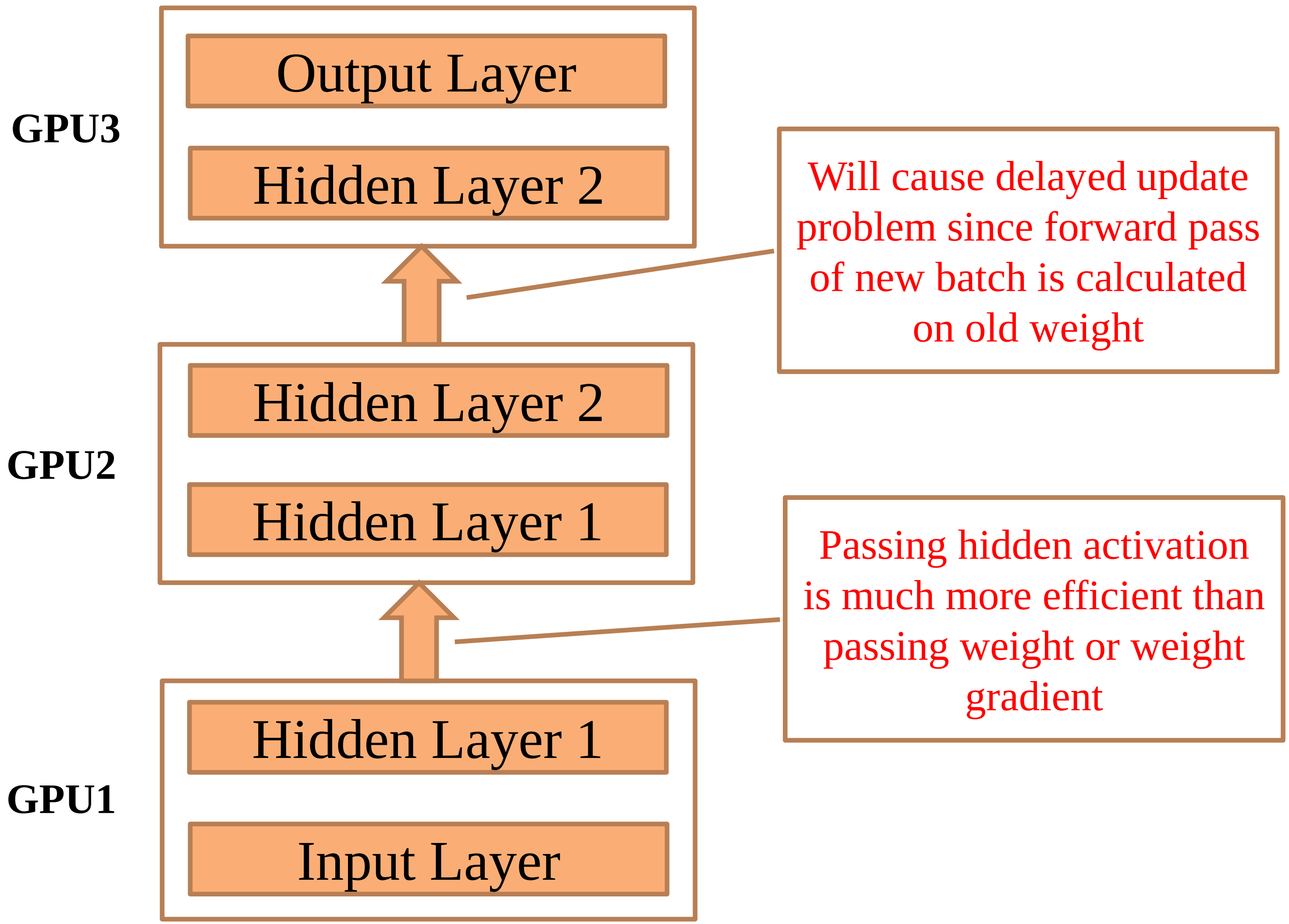
(Chen et al. 2012)



- Relative runtime for different minibatch sizes and GPU/server model types, and corresponding frame accuracy measured after seeing 12 hours of data (429:2kX7:9304).

Training (Multi-GPU): Pipeline

(Chen et al. 2012)



Training (Multi-GPU): Pipeline

(Chen et al. 2012)

parallelization method	#GPU K	minibatch size T 256	512	1024
none (baseline)	1	68	61	59
Multi-GPU with pipeline				
pipeline training (0..6; 7)	2	40	34	[[33]]
vs. (0..5; 6..7)	2	36	33	31
vs. (0..2; 3..4; 5..6; 7)	4	32	29	[27]
pipeline + striped top layer	4	20	18	[[18]]

- Training runtimes in minutes per 24h of data for different parallelization configurations. [[·]] denotes divergence, and [·] denotes a WER loss > 0.1% points on the Hub5 set (429:2kX7:9304).

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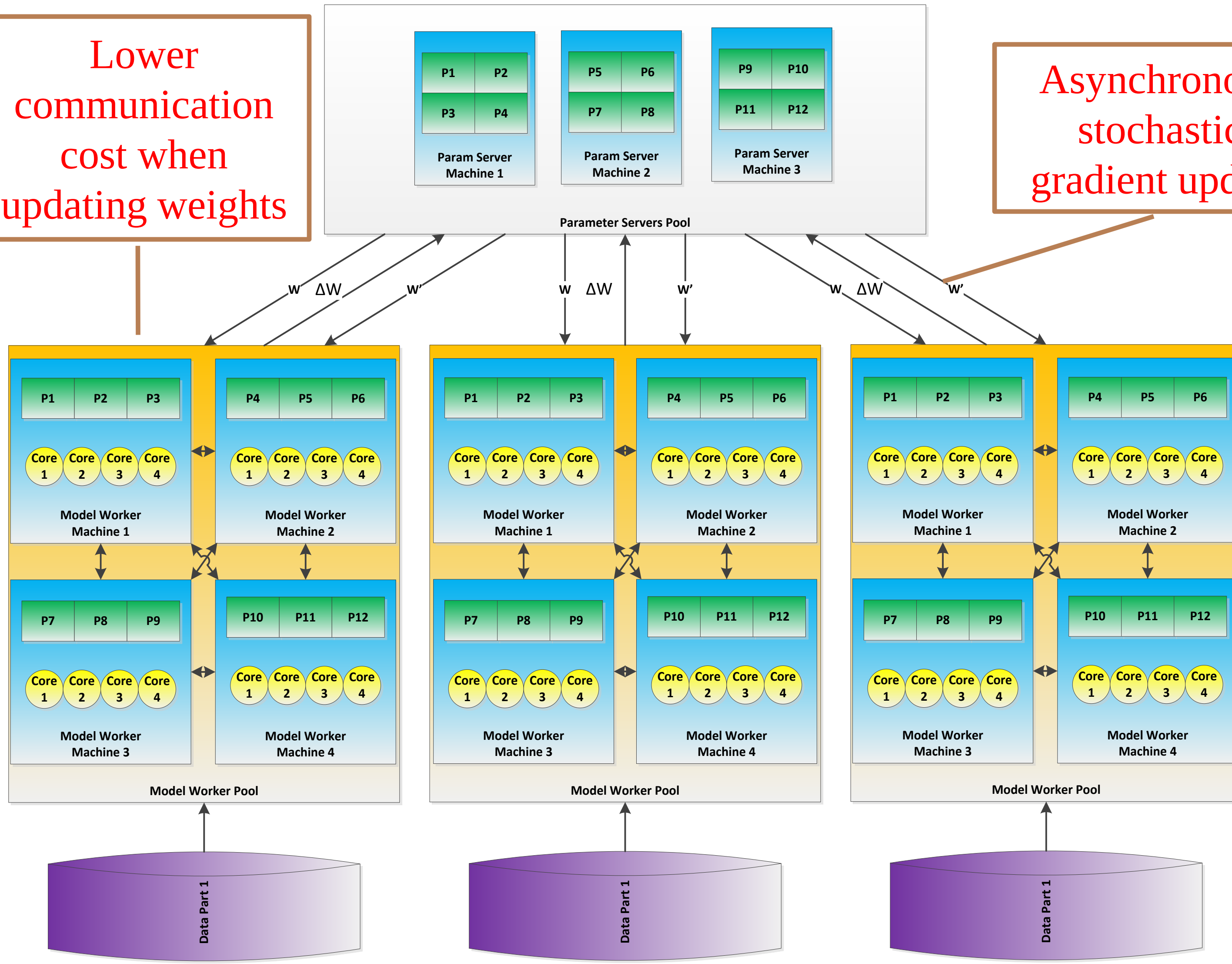
CD-DNN-HMM | Invariant Features | **Once Considered Obstacles** | Other Advances | Summary

Training (CPU Cluster)

(Dean et al. 2012, picture courtesy of Erdinc Basci)

Lower communication cost when updating weights

Asynchronous stochastic gradient update



Training (CPU or GPU Cluster)
(Kingsbury et al. 2012, Martens 2010)

- Use algorithms that are effective with large batches.
  - L-BFGS (work well if you use full batch)
  - Hessian free
- Simple data parallelization would work
- Key: the communication cost is small compared to the calculation

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Sequential Training

- Sequential training can achieve additional gain similar to MPE and BMMI on GMM
- State-level minimum Bayes risk (sMBR) seems to perform better than MMI and BMMI.
- **Table:** Broad cast news Dev-04f (Sainath et. al 2011)

Training Criterion	1504 senones
Frame-level Cross Entropy	18.5%
Sequence-level Criterion (sMBR)	17.0%

- **Table:** SWB (309-hr) (Kingsbury et al. 2012)

AM	Setup	Hub5'00-SWB	RT03S-FSH
SI GMM-HMM	BMMI+fMPE	18.9%	22.6%
SI DNN-HMM	7 x 2048 (frame CE)	16.1%	18.9%
SA GMM-HMM	BMMI+fMPE	15.1%	17.6%
SI DNN-HMM	7 x 2048 (sMBR)	13.3%	16.4%

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Take Advantage of More Senones

(Li et al. 2012)

- Senone set optimized for GMM-HMM is not optimal for CD-DNN-HMM.
- **Table:** SWB WER (%). The respective optimal choices are marked in bold-face for the development set (Hub5'00-SWB).

	GMM-HMM (ML)			CD-DNN-HMM		
#sen. (J)	Gaus-sians	Hub5'00 SWB	RT03S FSH	#hid. (N)	Hub5'00 SWB	RT03S FSH
309h (SWBD-I)						
9.0k	60	26.2	29.9	2k	17.2	19.8
11k	48	**26.1**	30.3	2k	17.1	19.5
15k	40	26.1	30.1	2k	17.2	19.5
18k	40	26.1	30.3	2k	16.7	19.3
22k	36	26.3	31.2	2k	16.7	19.4
27k	28	26.5	31.7	2k	**16.4**	19.4
32k	24	27.5	32.2	2k	16.4	19.5

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Flexible in Using Features

(Mohamed et al. 2012, Li et al. 2012)

- Information and features that cannot be effectively exploited within the GMM framework can now be exploited

Table: Comparison of different input features for DNN. All the input features are mean-normalized and with dynamic features. Relative WER reduction in parentheses.

Setup	WER (%)
CD-GMM-HMM (MFCC, fMPE+BMMI)	34.66 (baseline)
CD-DNN-HMM (MFCC)	31.63 (-8.7%)
CD-DNN-HMM (24 log filter-banks)	30.11 (-13.1%)
CD-DNN-HMM (29 log filter-banks)	30.11 (-13.1%)
CD-DNN-HMM (40 log filter-banks)	29.86 (-13.8%)
CD-DNN-HMM (256 log FFT bins)	32.26 (-6.9%)

Training set: VS-1 72 hours of audio.
Test set: VS-T (26757 words in 9562 utterances).
Both the training and test sets were collected at 16-kHz sampling rate.

Mixed Bandwidth ASR

(J. Li et. Al 2012)

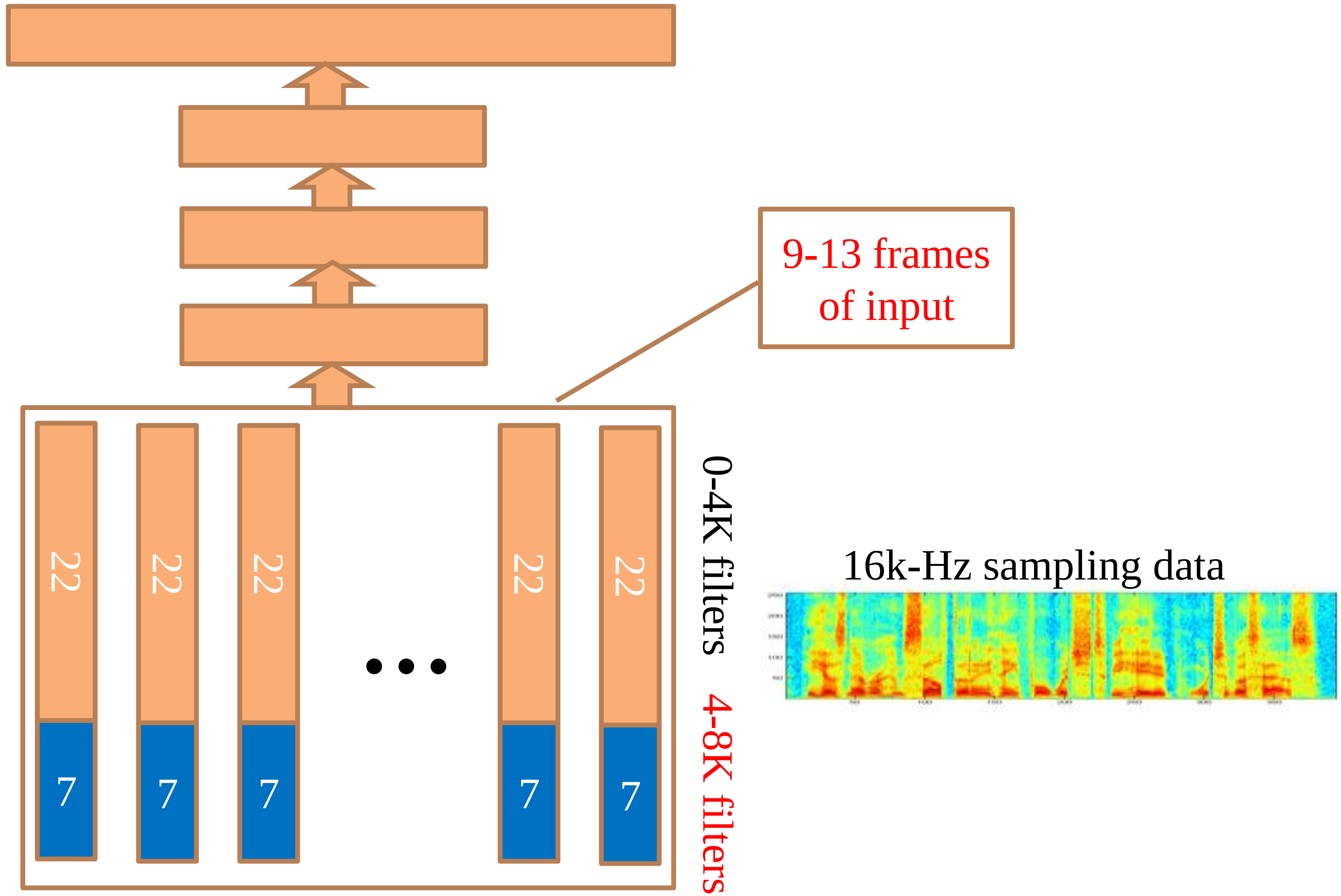

Figure: DNN training/testing with 16-kHz and 8-kHz sampling data

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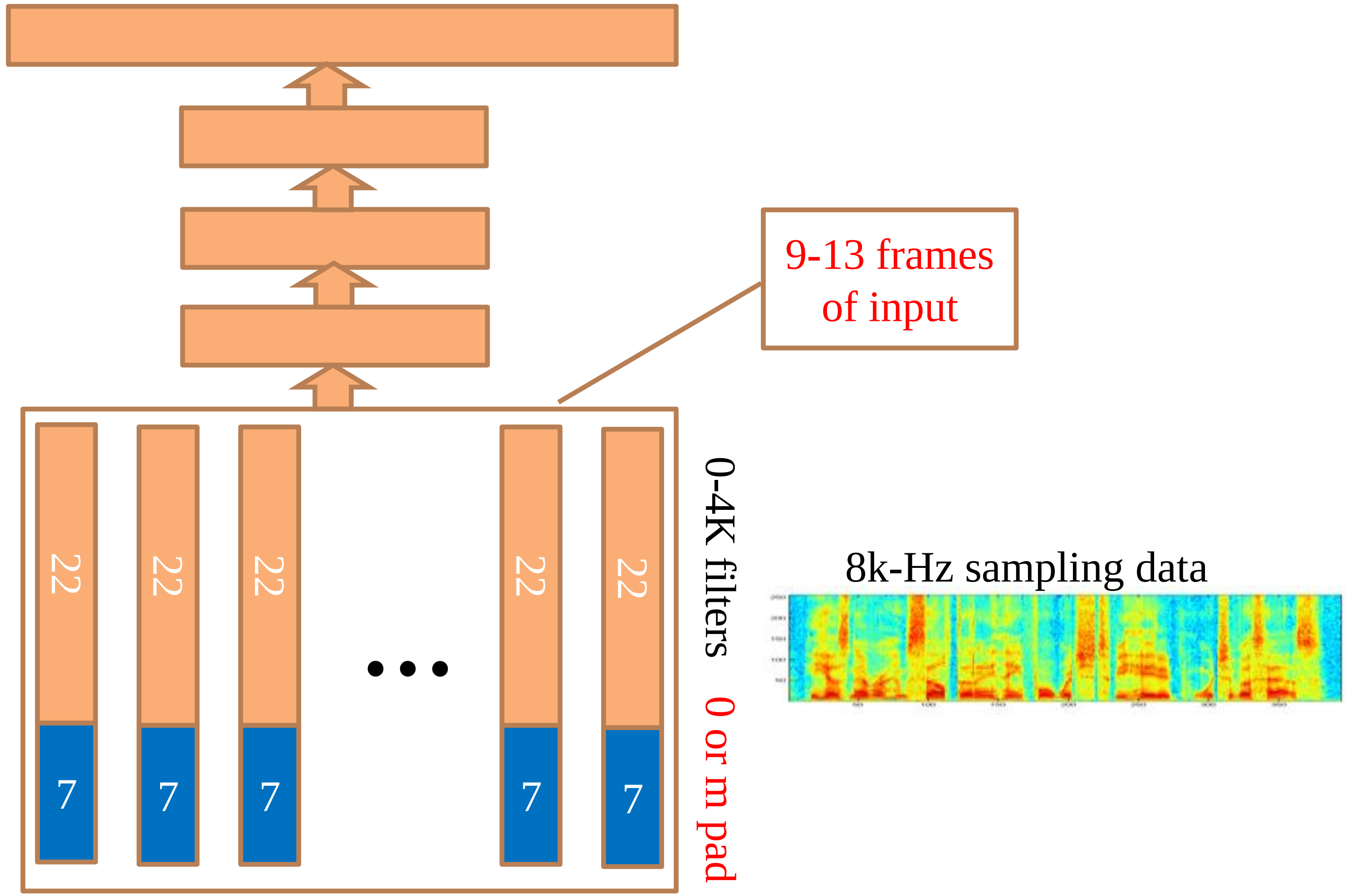

Figure: DNN training/testing with 16-kHz and 8-kHz sampling data

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Table: DNN performance on wideband and narrowband test sets using mixed-bandwidth training data.

Training Data	WER (16-kHz VS-T)	WER (8-kHz VS-T)
16-kHz VS-1 (B1)	**29.96**	71.23
8-kHz VS-1 + 8-kHz VS-2 (B2)	-	**28.98**
16-kHz VS-1 + 8-kHz VS-2 (ZP)	**28.27**	29.33
16-kHz VS-1 + 8-kHz VS-2 (MP)	28.36	29.37
16-kHz VS-1 + 16-kHz VS-2 (UB)	**27.47**	53.51

B1: baseline 1
B2: baseline 2
ZP: zero padding
MP: mean padding
UB: upper bound
Mixed-bandwidth: recover 2/3 of (UB-B1) and ½ of (UB-B2)

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Table: The Euclidean distance (ED) for the output vectors at each hidden layer (L1-L7) and the KL-divergence (in nats) for the posterior vectors at the top layer between 8-kHz and 16-kHz input features

	16-kHz DNN (UB)		**Data-mix DNN (ZP)**	
Layer	Mean (ED)	Variance (ED)	Mean (ED)	Variance (ED)
L1	13.28	3.90	7.32	3.62
L2	10.38	2.47	5.39	1.28
L3	8.04	1.77	4.49	1.27
L4	8.53	2.33	4.74	1.85
L5	9.01	2.96	5.39	2.30
L6	8.46	2.60	4.75	1.57
L7	5.27	1.85	3.12	0.93
Layer	Mean (KL)		Mean (KL)	
Top layer	2.03		0.22	

Noise Robustness

(Look for our ICASSP 2013 paper for details)

- DNN converts input features into more invariant and discriminative features
- Robust to environment and speaker variations
- Aurora 4 16kHz medium vocabulary noise robustness task
  - Training: 7137 utterances from 83 speakers
  - Test: 330 utterances from 8 speakers

Table: WER (%) Comparison on Aurora4 (16k Hz) Dataset.

Setup	Set A	Set B	Set C	Set D	Avg
GMM-HMM (Baseline)	12.5	18.3	20.5	31.9	23.9
GMM-HMM (MPE + VAT)	7.2	12.8	11.5	19.7	15.3
GMM-HMM + Structured SVM	7.4	12.6	10.7	19.0	14.8
CD-DNN-HMM (2kx7)	(Look for our ICASSP 2013				13.7
CD-DNN-HMM (2kx7)	paper for details)				12.9

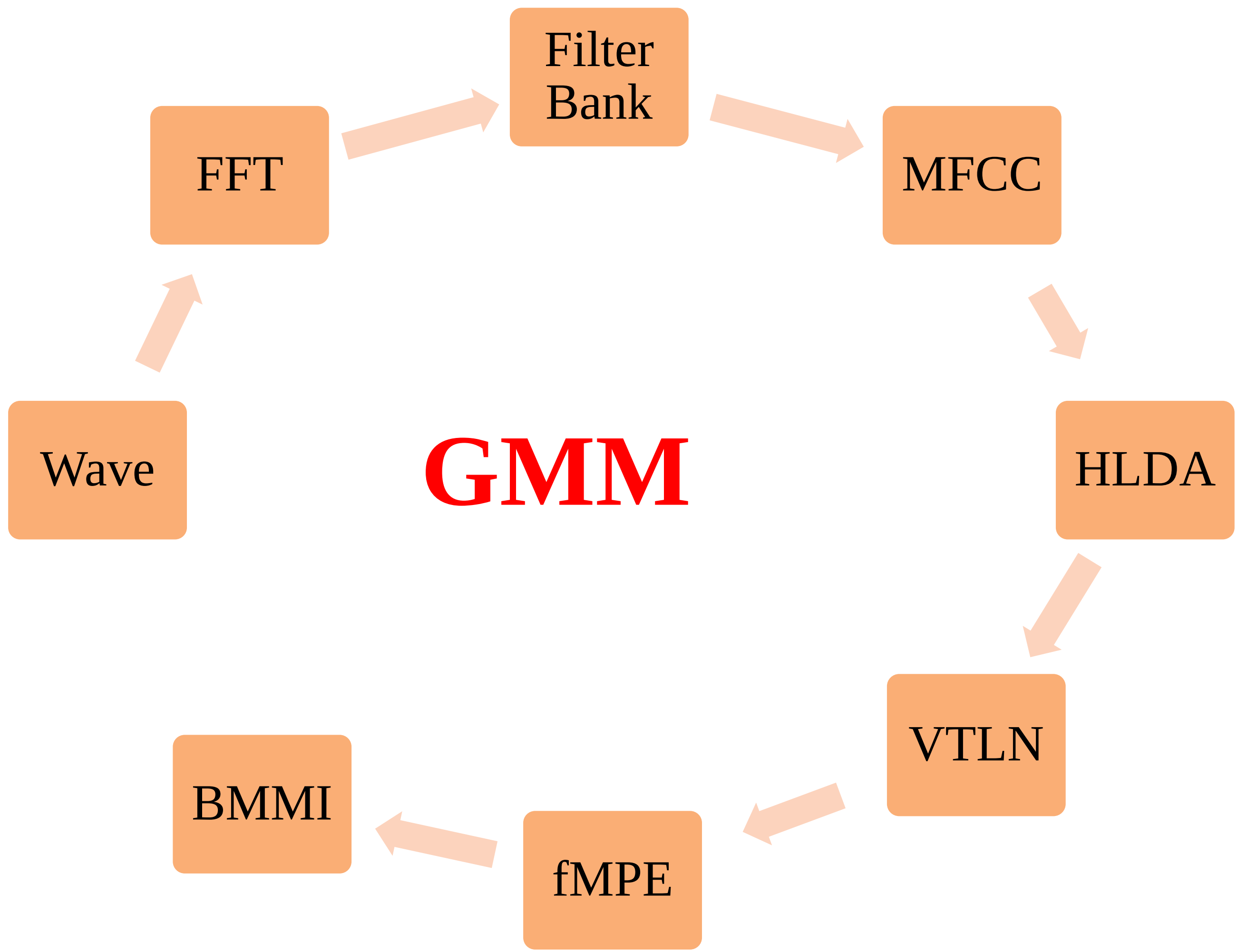
Outline

- CD-DNN-HMM
- Invariant Features
- Once Considered Obstacles
- Other Advances
- **Summary**

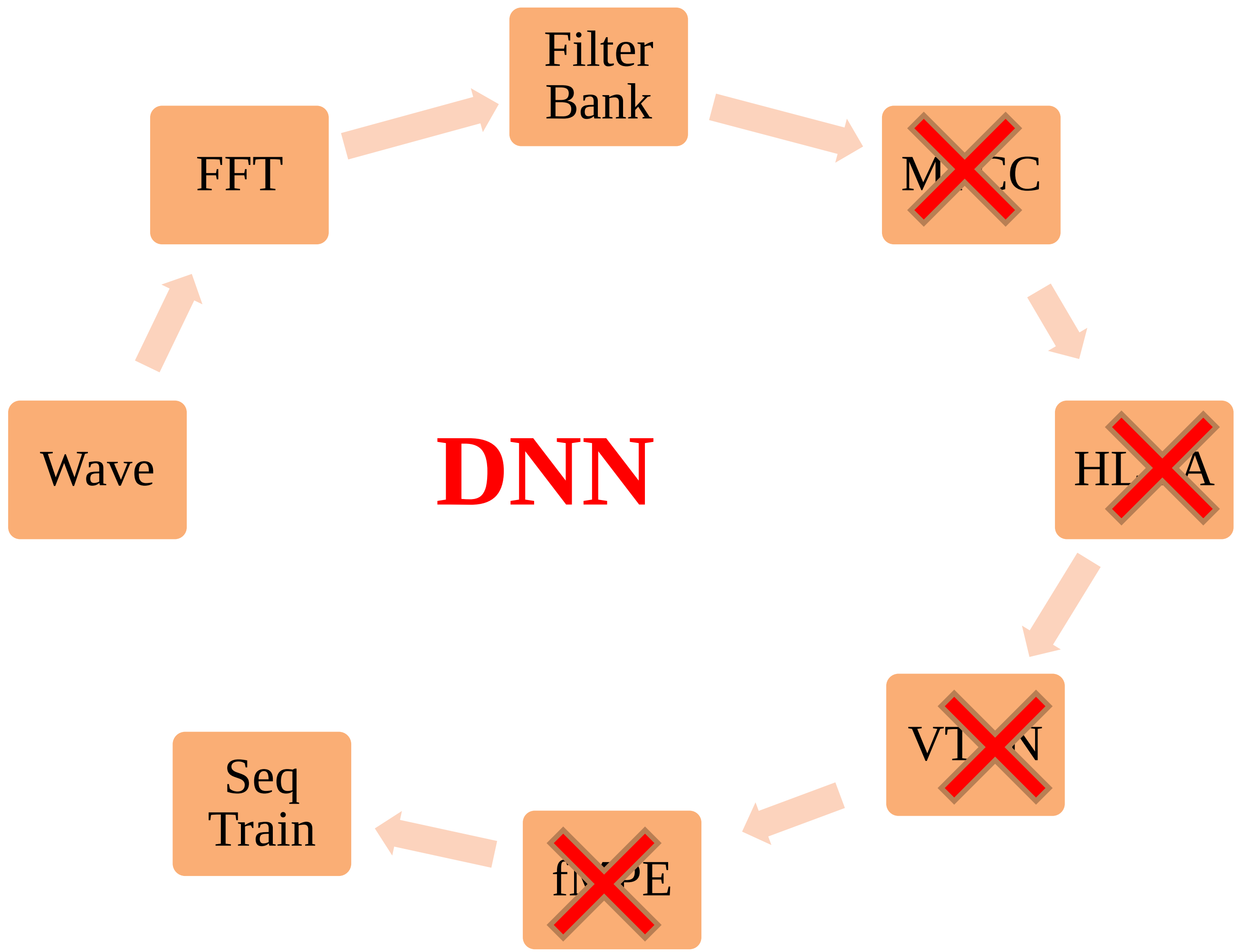
Who Can Understand Your Speech Better?

- DNN already outperforms GMM in many tasks
  - Deep neural network is more powerful than the shallow models including GMMs
  - Features learned by DNNs are more invariant and selective
  - DNNs can exploit more info and features difficult to exploit in the GMM framework
- Many speech groups (Microsoft, Google, IBM) are adopting it.
- Commercial deployment of DNN systems is practical now
  - Many once considered obstacles for adopting DNNs have been removed
  - Already commercially deployed by Microsoft and Google
  - Rick's demo indicates it can play important role in S2S translation

To Build a State-Of-the-Art System



Better Accuracy and Simpler



Multilingual S2S Translation

(Look for our ICASSP 2013 paper for first step results)

Thank You

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