Why Deep Neural Network Works for Speech Recognition?

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Outline

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- Introduction
  - Automatic Speech Recognition (ASR)
  - Deep Neural Network (DNN)
- DNN/HMM for Speech
- Bottleneck Features
- Incoherent Training
- Conclusions

Introduction: ASR History

- ASR formulation:
  - GMM/HMM + n-gram + Viterbi search
- Technical advances (incremental) over past 10 years:
  - Adaptation (speaker/environment): 5% *rel.* gain
  - Discriminative Training: 5-10% *rel.* gain
  - Feature normalization: 5% *rel.* gain
  - ROVER: 5% *rel.* gain
- More and more data ➔ better and better accuracy
  - read speech (>90%), telephony speech (>70%)
  - meeting/voicemail recording (<60%)

Acoustic Modeling: Optimization

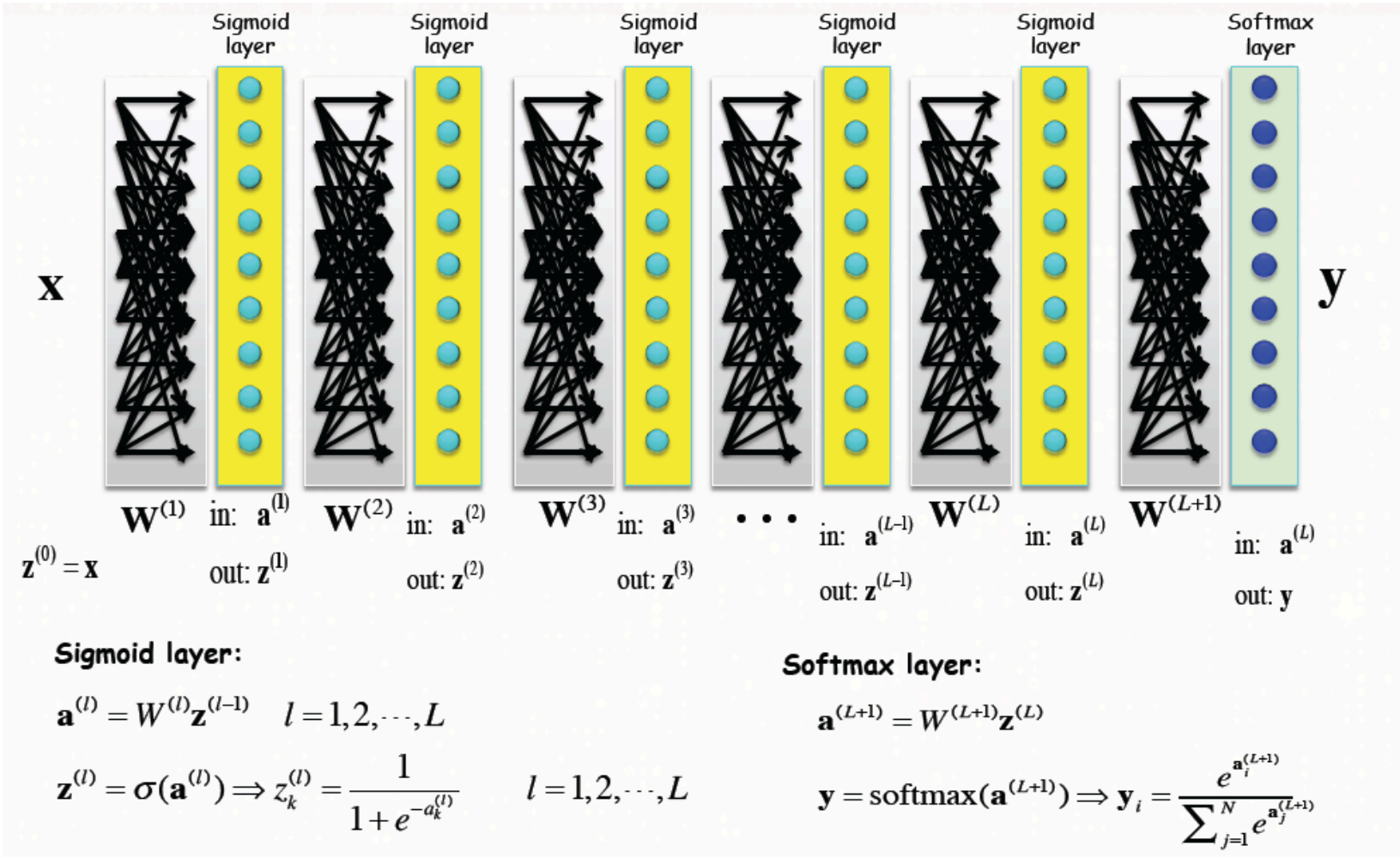
- Acoustic modeling → large-scale optimization
  - 2000+ hour data → GMMs/HMM

    billions of samples → 10+ million free parameters
- Training Methods
  - Maximum Likelihood Estimation (MLE)
  - Discriminative Training (DT)
- Engineering Issues
  - Efficiency: feasible with 100-1000 of CPUs
  - Reliability: robust estimation of all parameters

Neural Network for ASR

- **1990s: MLP for ASR** *(Bourlard and Morgan, 1994)*
  - **NN/HMM hybrid model (worse than GMM/HMM)**
- **2000s: TANDEM** *(Hermansky, Ellis, et al., 2000)*
  - **Use MLP as Feature Extraction (5-10% rel. gain)**
- **2006: DNN for small tasks** *(Hinton et al., 2006)*
  - **RBM-based pre-training for DNN**
- **2010: DNN for small-scale ASR** *(Mohamed, Yu, et al. 2010)*
- **2011: DNN for large-scale ASR**
  - **Over 30% rel. gain in Switchboard** *(Seide et al., 2011)*

Deep Neural Network (DNN)



Sigmoid layer:

$$\mathbf{a}^{(l)} = W^{(l)}\mathbf{z}^{(l-1)} \qquad l = 1, 2, \cdots, L$$

$$\mathbf{z}^{(l)} = \sigma(\mathbf{a}^{(l)}) \Rightarrow z_k^{(l)} = \frac{1}{1+e^{-a_k^{(l)}}} \qquad l = 1, 2, \cdots, L$$

Softmax layer:

$$\mathbf{a}^{(L+1)} = W^{(L+1)}\mathbf{z}^{(L)}$$

$$\mathbf{y} = \text{softmax}(\mathbf{a}^{(L+1)}) \Rightarrow \mathbf{y}_i = \frac{e^{\mathbf{a}_i^{(L+1)}}}{\sum_{j=1}^{N} e^{\mathbf{a}_j^{(L+1)}}}$$

DNN Training (I)

Given a training set $X=\{\mathbf{x}_t, l_t,\ t=1,2\cdots T\}$, optimize the objective function:

$$Q(\mathbf{W})=\sum_{t=1}^{T}Q_t(\mathbf{W})=\sum_{t=1}^{T}\sum_{i=1}^{N}[-\delta(l_t-i)\cdot\ln \mathbf{y}_i(\mathbf{x}_t,\mathbf{W})]$$

Define error signals in each layer $e_{tk}^{(l)}=\frac{\partial}{\partial a_k^{(l)}}Q_t(W)=\frac{-1}{y_{l_t}(\mathbf{x}_t,\mathbf{W})}\frac{\partial y_{l_t}(\mathbf{x}_t,\mathbf{W})}{\partial a_k^{(l)}}$

Softmax layer l=L+1

$$e_{tk}^{(L+1)}=\frac{-1}{y_{l_t}(\mathbf{x}_t,\mathbf{W})}\frac{\partial y_{l_t}(\mathbf{x}_t,\mathbf{W})}{\partial a_k^{(L+1)}}=y_k-\delta(l_t-k)$$

Sigmoid layer l=1,2,…,L

$$e_{tk}^{(l)}=\frac{\partial Q_t(W)}{\partial a_k^{(l)}}=\sum_{j=1}^{N}\frac{\partial Q_t(W)}{\partial a_j^{(l+1)}}\frac{\partial a_j^{(l+1)}}{\partial a_k^{(l)}}=\sum_{j=1}^{N}e_{tj}^{(l+1)}\frac{\partial a_j^{(l+1)}}{\partial a_k^{(l)}}=\sum_{j=1}^{N}e_{tj}^{(l+1)}\cdot z_k^{(l)}\cdot(1-z_k^{(l)})\cdot W_{kj}^{(l+1)}$$

$$=z_k^{(l)}\cdot(1-z_k^{(l)})\cdot\sum_{j=1}^{N}e_{tj}^{(l+1)}W_{jk}^{(l+1)}$$

DNN Training (II)

Given a training set $\mathrm{X}=\{\mathbf{x}_t, l_t,\ t=1,2\cdots T\}$

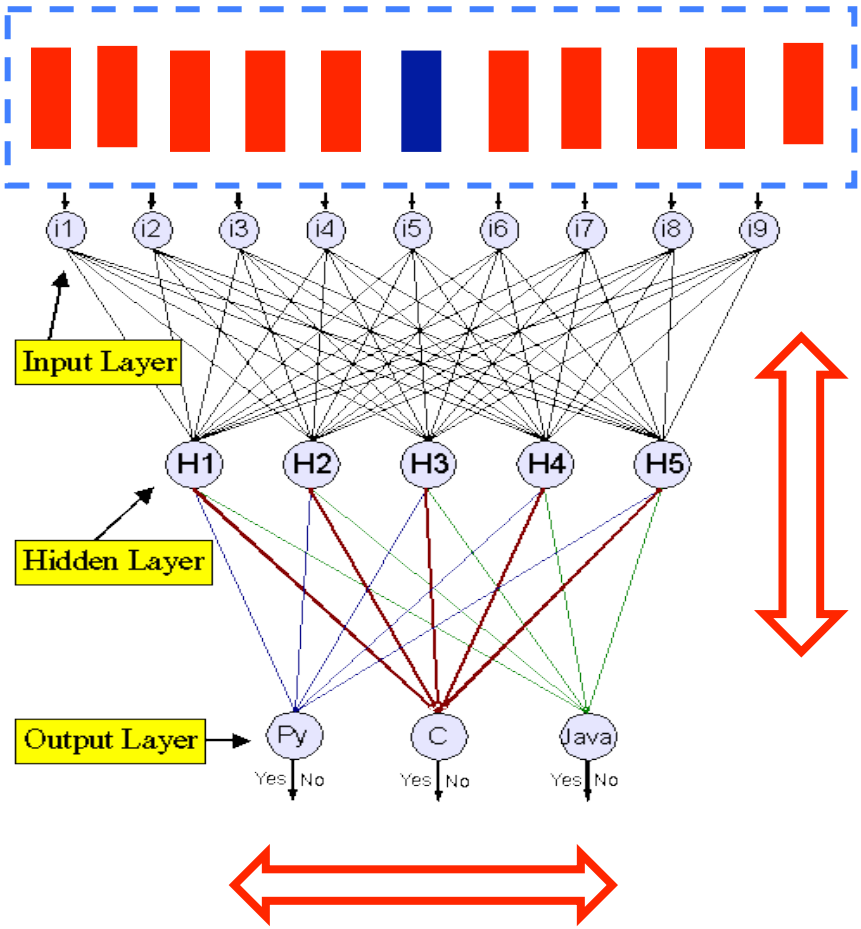
$$Q(\mathbf{W}) = -\sum_{t=1}^{T} Q_t(\mathbf{W}) = -\sum_{t=1}^{T}\sum_{i=1}^{N} \delta(l_t - i)\cdot \ln \mathbf{y}_i(\mathbf{x}_t, \mathbf{W})$$

$$\frac{\partial}{\partial \mathbf{w}_k^{(l)}} Q_t(\mathbf{W}) = \frac{\partial Q_t(\mathbf{W})}{\partial a_k^{(l)}} \frac{\partial a_k^{(l)}}{\partial \mathbf{w}_k^{(l)}} = e_{tk}^{(l)} \cdot \mathbf{z}_t^{(l-1)}$$

Use stochastic gradient Descent (SGD) to update weight vectors:

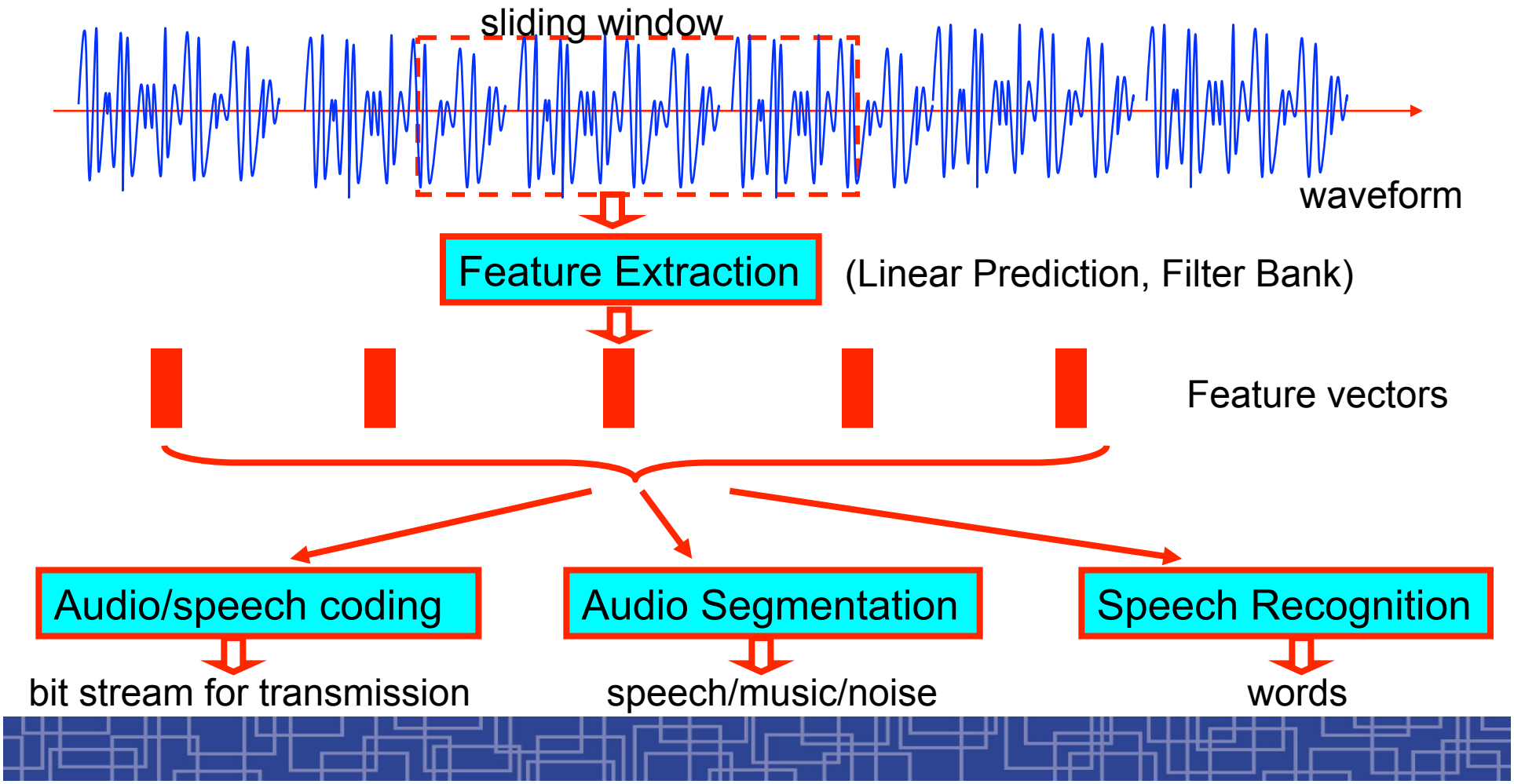
$$\mathbf{w}_k^{(l)} \leftarrow \mathbf{w}_k^{(l)} - \eta \frac{\partial}{\partial \mathbf{w}_k^{(l)}} Q_t(\mathbf{W}) = \mathbf{w}_k^{(l)} - \eta \cdot e_{tk}^{(l)} \cdot \mathbf{z}_t^{(l-1)}$$

NN for ASR: old and new

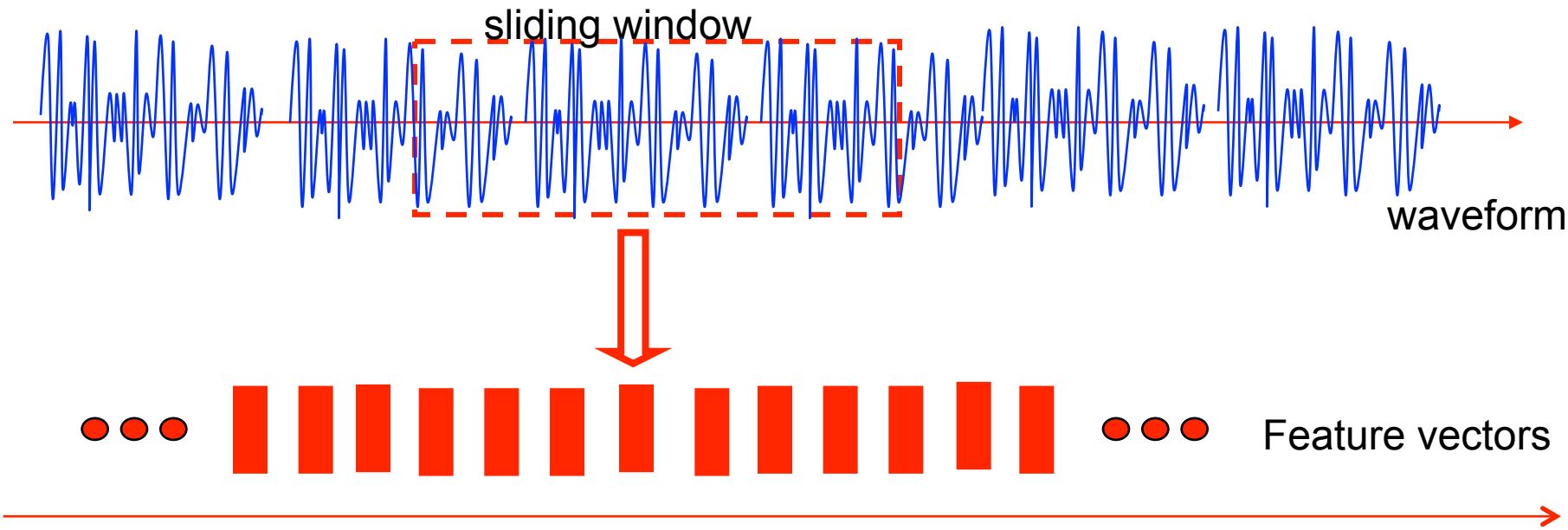


- Deeper network
  - more hidden layers
  - (1 → 6-7 layers)
- Wider network
  - More hidden nodes
  - More output nodes
  - (100 → 5-10 K)
- More data
  - 10-20 hours → 300 to 10k+ hours of training data

ASR Frontend



Short-time Analysis



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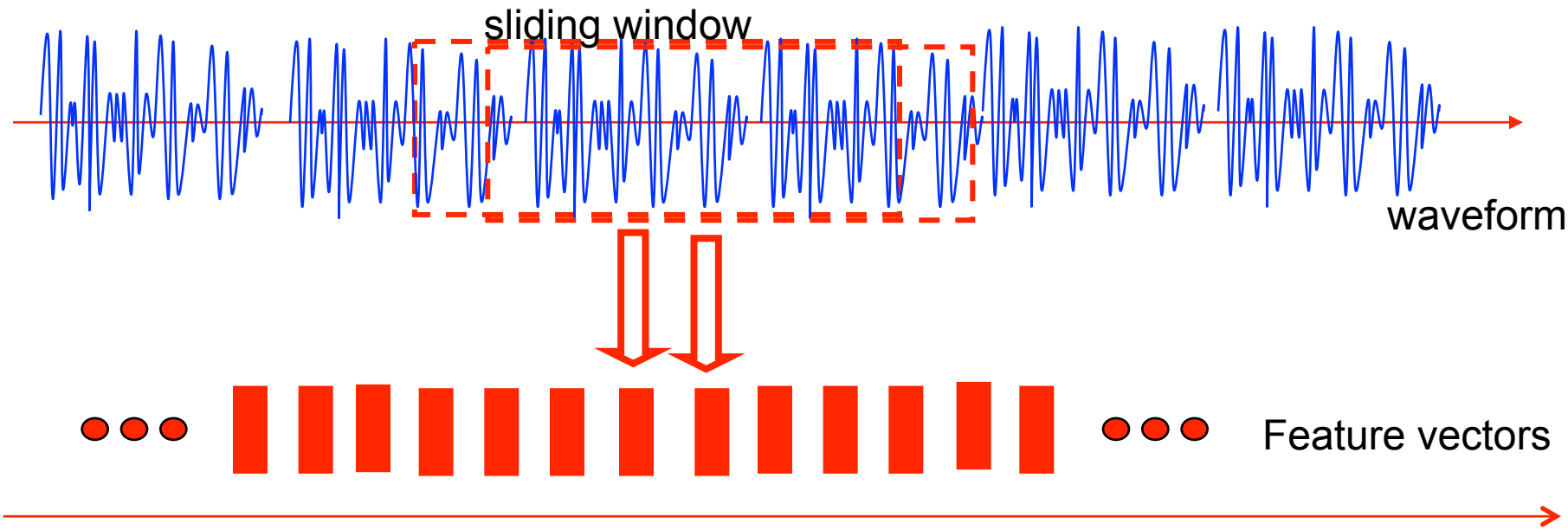

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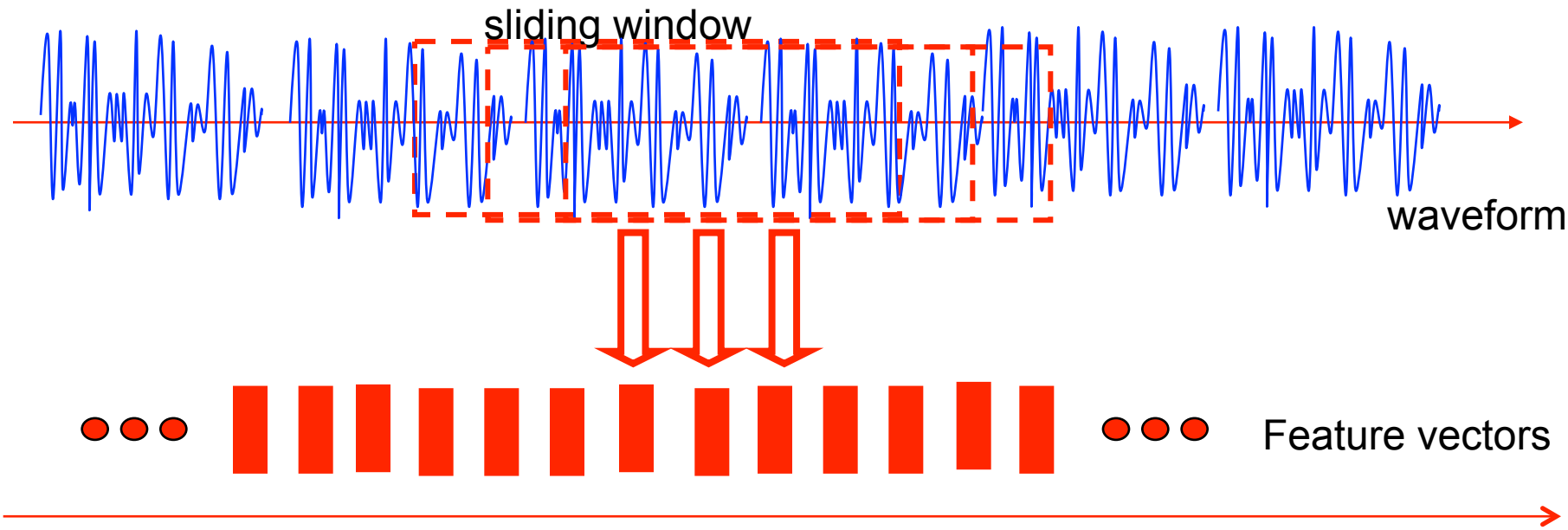
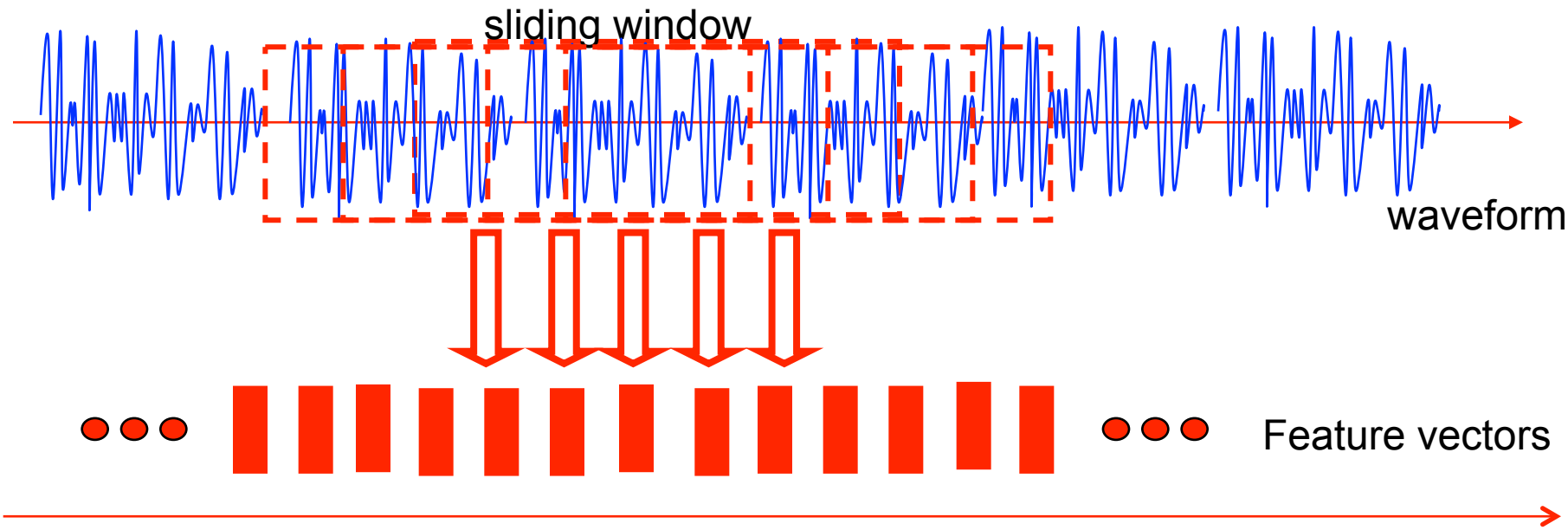
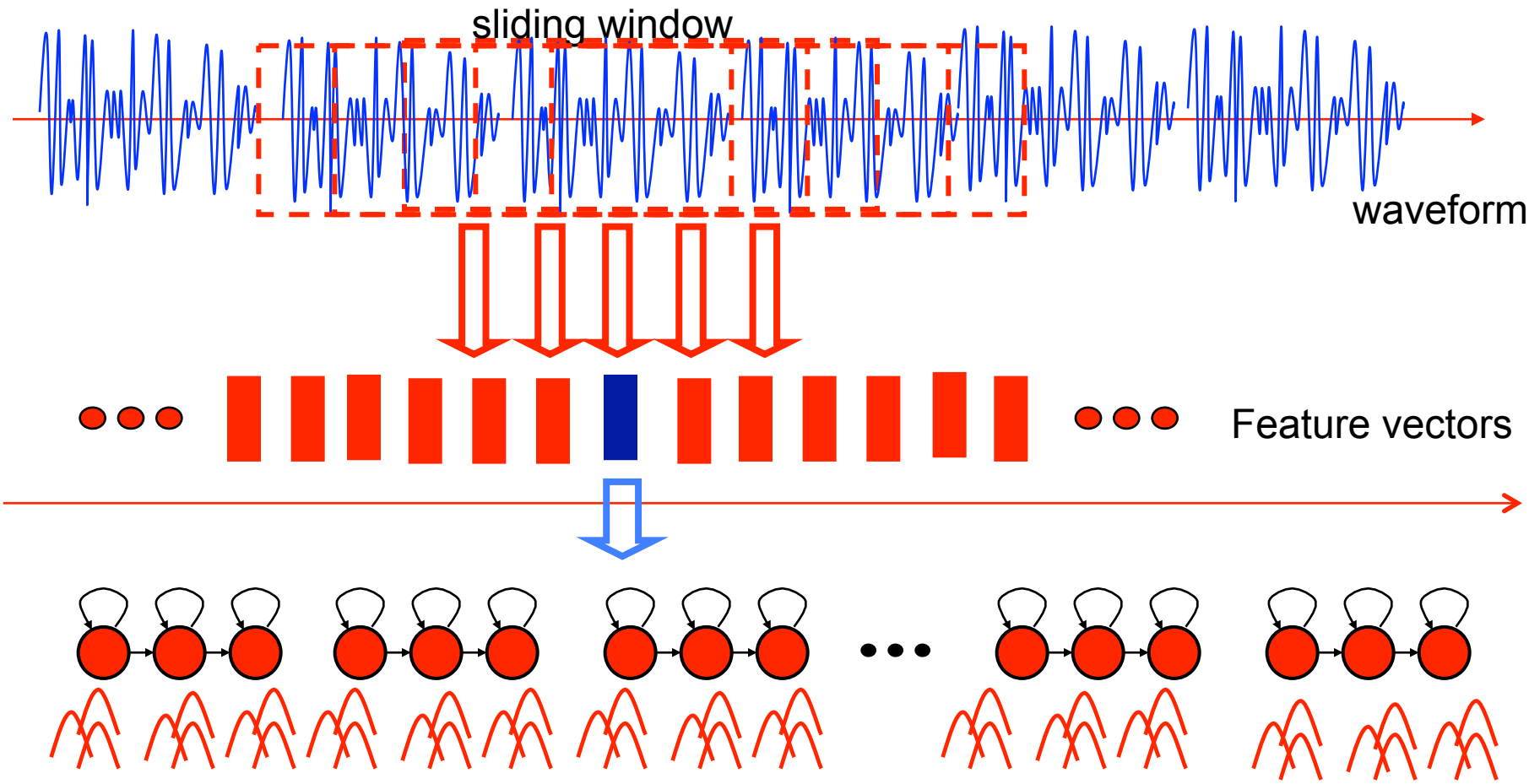


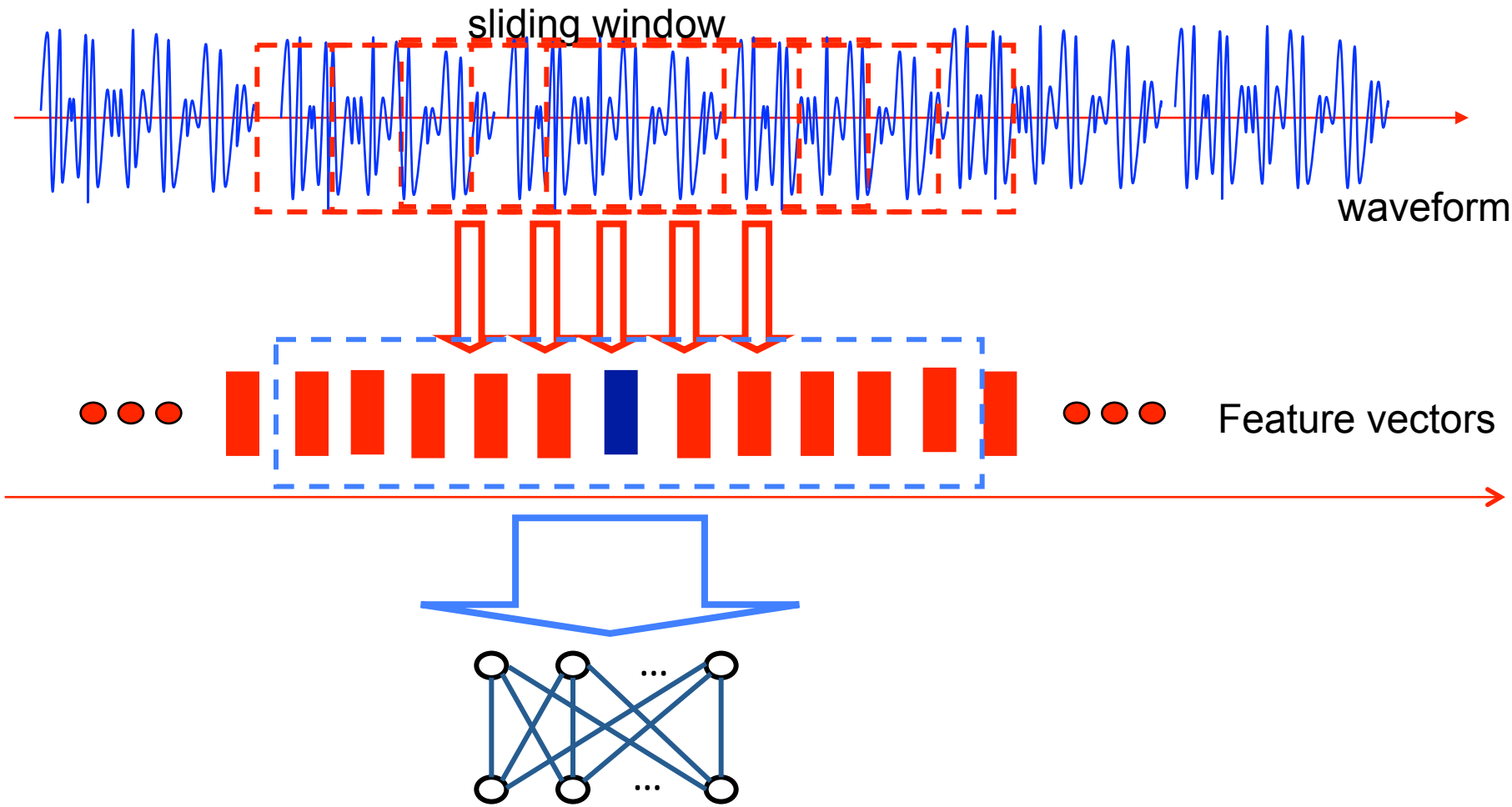
Short-time Analysis



ASR Frontend: GMM/HMM

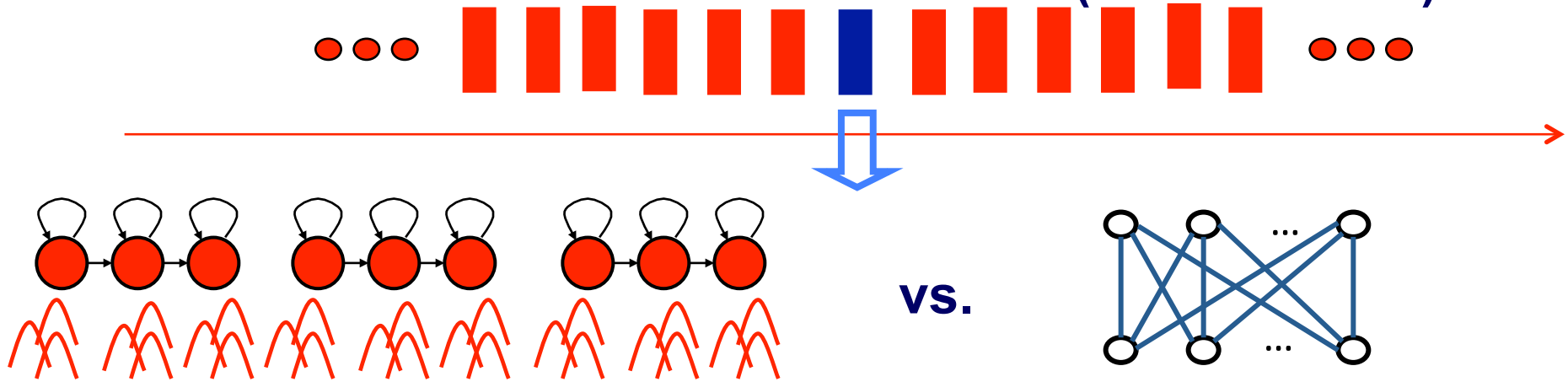


ASR Frontend: NN/HMM



GMMs/HMM vs. DNN/HMM

- Different acoustic models
  - GMMs vs. DNN
- Different feature vectors
  - 1 frame vs. concatenated frames (11-15 frames)



Experiment (I): GMMs/HMM vs. DNN/HMM

- In-house 70-hour Mandarin ASR task;
- GMM: 4000 tied HMM states, 30 Gaussians per state
- DNN: pre-trained; 1024 nodes per layer; 1-6 hidden layers

Numbers in word error rates (%)
NN-1: 1 hidden layer; DNN-6: 6 hidden layers
MPE-GMM: discriminatively trained GMM/HMM

Context window	NN-1	DNN-6	MPE-GMM
1	18.0	17.0	16.7
Context window	3	5	7
DNN-6	14.2	13.7	13.5
Context window	9	11	13
DNN-6	13.5	13.4	13.6

Experiment (II): GMMs/HMM vs. DNN/HMM

- 300-hour Switchboard task, Hub5e01 test set
- GMM: 8991 tied HMM states, 40 Gaussian per state
- DNN: pre-trained; 2048 nodes per layer; 1-5 hidden layers

Word error rates (WER) in Hub01 test set (%)
NN-1: 1 hidden layer; DNN-3/5: 3/5 hidden layers
MPE-GMM: discriminatively trained GMM/HMM

context window	MPE GMM	NN-1	DNN-3	DNN-5
1	32.8%	35.4%	34.8%	33.1%
11	n/a	31.4%	25.6%	23.7%

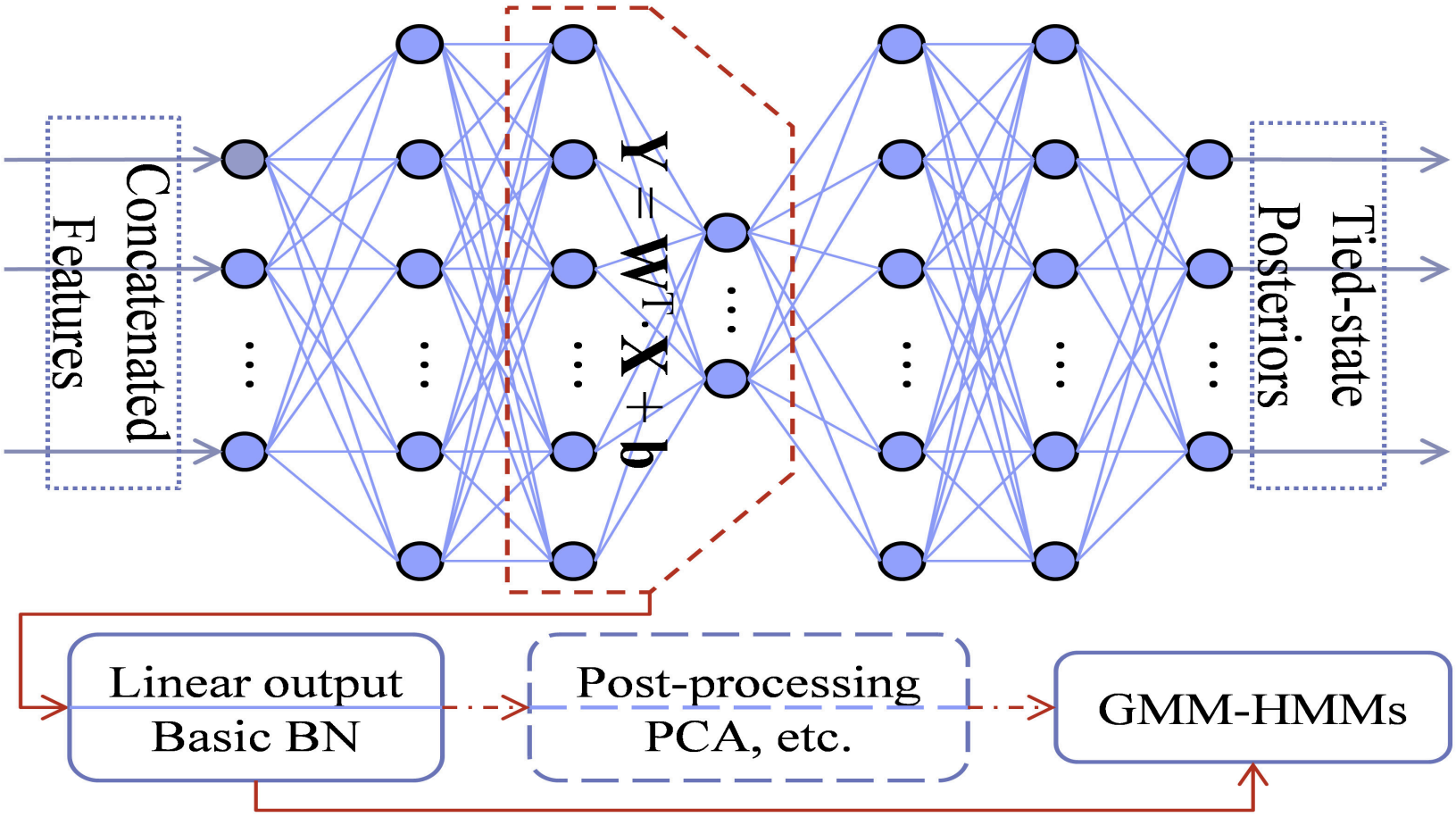
Conclusions (I)

- The gain of DNN/HMM hybrid is almost entirely attributed to the concatenated frames.
  - The concatenated features contain almost all additional information resulting in the gain.
  - But they are highly correlated.
- DNN is powerful to leverage highly correlated features.

What's next

- How about GMM/HMM?
- Hard to explore highly correlated features in GMMs.
  - Requires dimensional reduction for de-correlation.
- Linear dimensional reduction (PCA, LDA, KLT, …)
  - Failed to compete with DNN.
- Nonlinear dimensional reduction
  - Using NN/DNN *(Hinton et al.)*, a.k.a. bottleneck features
  - Manifold learning, LLE, MDS, SNE, …?

Bottleneck (BN) Feature



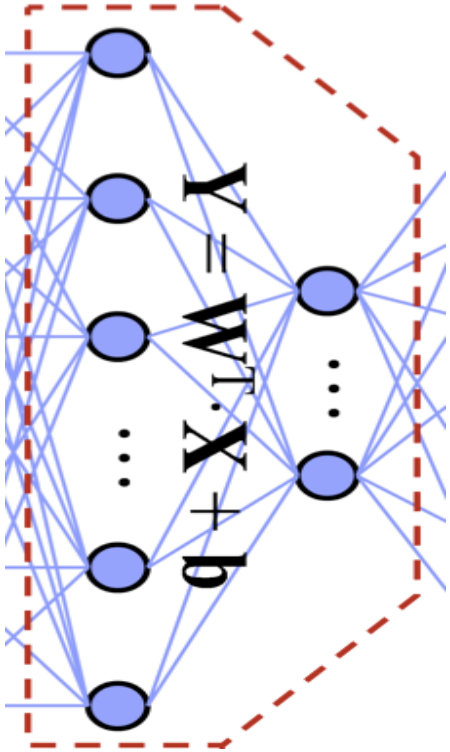
Experiments: BN vs. DNN

300-hour English Switchboard Task (WER in %)
MLE: maximum likelihood estimation; MPE: discriminative training
ReFA: realigned class labels; DT: sequence training of DNNs
DT+BN: BN features extracted from sequence-trained BN networks

Acoustic models (Features)	Hub5e01		Hub5e00	
	MLE	MPE	MLE	MPE
GMM-HMMs (PLP)	35.4%	32.8%	28.7%	24.7%
GMM-HMMs (BN)	26.0%	23.2%	17.9%	15.9%
DNN (11 PLPs)	23.7%		16.7%	
DNN (ReFA+DT)	--		14.0%	
GMM-HMMs (DT+BN)	--		16.6%	14.6%

Incoherent Training

- Bottleneck (BN) works but:
  - BN hurts DNN performance a little
  - Increasing BN ➔ correlation up
- Can we do better?
- The Idea: embedding de-correlation into back-propagation of DNN training.
  - De-correlation by constraining columns of weight matrix *W*
  - How to constrain?



Incoherent Training

- **Define coherence of DNN weight matrix *W* as:**

$$G_W = \max_{i,j} g_{ij} = \max_{i,j} \frac{\left| w_i \cdot w_j \right|}{\left\| w_i \right\| \left\| w_j \right\|}$$

- **A matrix with smaller coherence indicates all of its column vectors are less similar.**
- **Approximate coherence using soft-max:**

$$G_W = \log \left(\frac{1}{M} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \exp\{\beta \cdot g_{ij}\} \right)^{\frac{1}{\beta}}$$

Incoherent Training

- All DNN weight matrices are optimized by minimizing a regularized objective function:

$$F^{(new)} = F^{(old)} + \alpha \cdot \max_{W} G_W$$

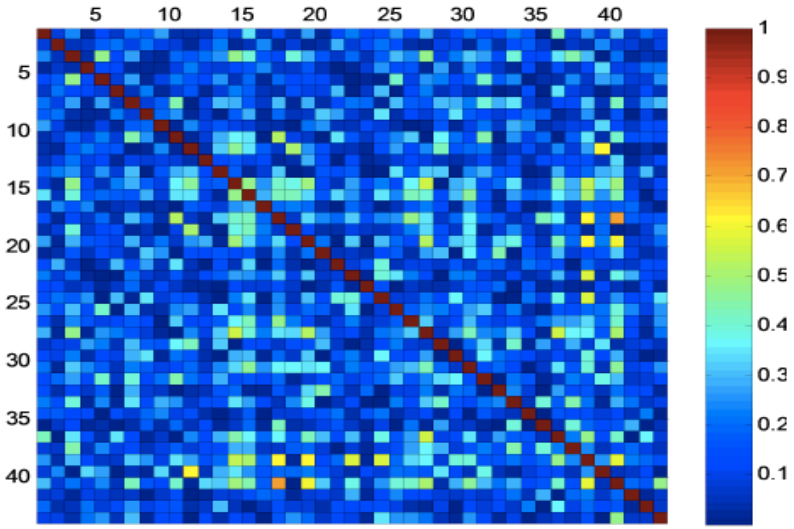
- Derivatives of coherence:

$$\frac{\partial G_W}{\partial w_k} = \sum_{j=1}^{N} \gamma_{kj} g_{kj} \left[\frac{\mathbf{w}_j}{\mathbf{w}_k \cdot \mathbf{w}_j} - \frac{\mathbf{w}_k}{\mathbf{w}_k \cdot \mathbf{w}_k} \right]$$

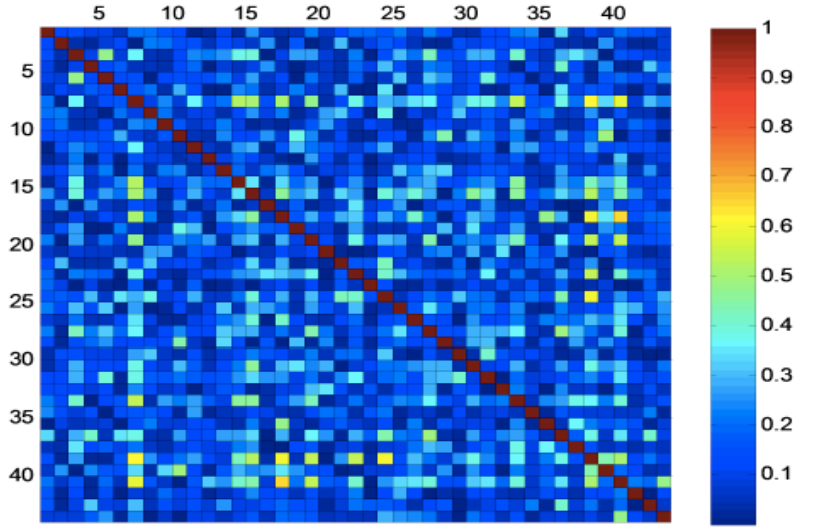
- Back-propagation is still applicable…

Incoherent Training: De-correlation

Applying incoherent training to one weight matrix in BN



(a) Baseline BN



(b) Weight-matrix Incoherent BN

Incoherent Training: Data-driven

- If only applying to one weight matrix *W*: $Y = W^T X + b$
- Covariance matrix of Y: $C_Y = W^T C_X W$
- Directly measure correlation coefficients based on the above covariance matrix:

$$G_W = \max_{i \neq j} g_{ij}$$

with $$g_{ij} = \frac{\left|(\mathbf{w}_i)^\top \mathbf{C_X} \mathbf{w}_j\right|}{\sqrt{(\mathbf{w}_i)^\top \mathbf{C_X} \mathbf{w}_i} \cdot \sqrt{(\mathbf{w}_j)^\top \mathbf{C_X} \mathbf{w}_j}}$$

Cx is estimate from one mini-batch each time

Incoherent Training: Data-driven

- After *soft-max*, Derivatives can be computed as:

where

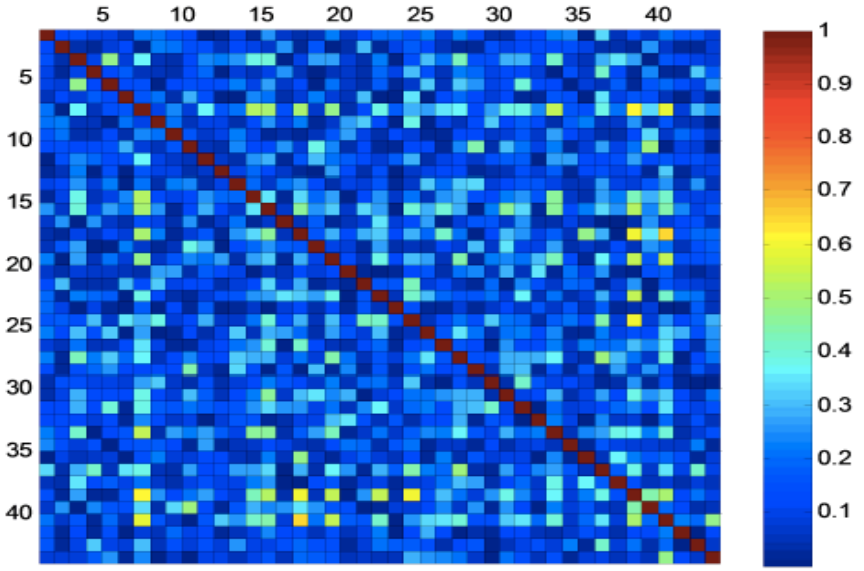
$$\frac{\partial G_W}{\partial w_k} = \frac{\sum_{j \neq k}^{N} \left[\exp\{\beta \cdot g_{kj}\} \cdot \frac{\partial g_{kj}}{\partial \mathbf{w}_k} \right]}{\sum_{i=1}^{N} \sum_{j=i+1}^{N} \exp\{\beta \cdot g_{ij}\}}$$

$$\frac{\partial g_{kj}}{\partial \mathbf{w}_k} = g_{kj} \left[\frac{\mathbf{C_X w}_j}{(\mathbf{w}_k)^\top \mathbf{C_X w}_j} - \frac{\mathbf{C_X w}_k}{(\mathbf{w}_k)^\top \mathbf{C_X w}_k} \right]$$

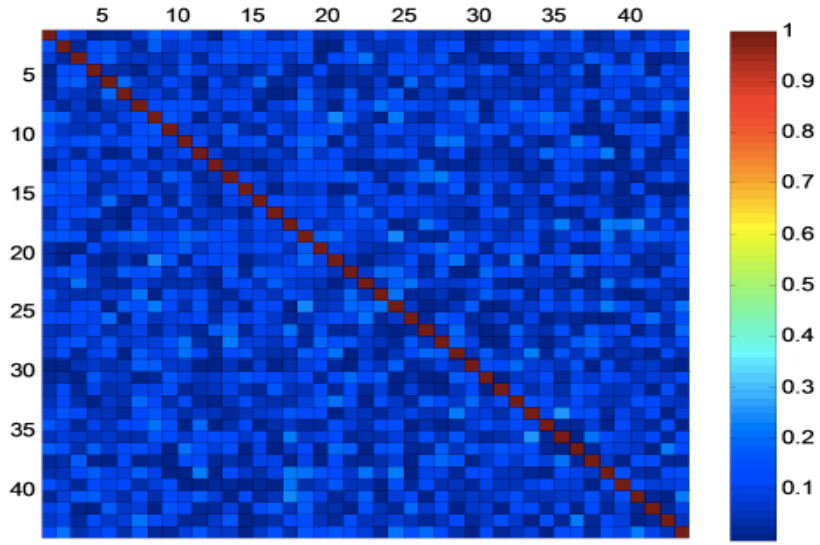
- Back-propagation still applies except Cx is computed for each mini-batch

Incoherent Training: Data-driven De-correlation

When applying Incoherent Training to one weight matrix



(b) Weight-matrix Incoherent BN



(c) Mini-batch-data Incoherent BN

Experiment: Incoherent Training

300-hour English Switchboard Task, WER (%) on Hub5e01
DNN: 6 hidden layers of 2048 nodes
BN: extracted from 5 hidden layers of bottleneck DNN

BN Feature / models	MLE	MPE
DNN	23.7%	
Baseline BN	26.0%	23.2%
Weight-Matrix Incoherent BN	25.7%	--
Mini-batch-data Incoherent BN	25.6%	22.8%

Conclusions (II)

- Possible to compete with DNN under the traditional GMMs/HMM framework.
- Promising to use bottleneck features learned from the proposed incoherent training.
- Benefits over DNN/HMM:
  - Slightly better performance
  - Enjoy other ASR techniques (adaptation, …)
  - Faster training process
  - Faster decoding process

Future Work

- Apply incoherent training to general DNN learning.
- Consider other nonlinear dimensional reduction methods for concatenated features.

Other Ongoing DNN Projects

- Convolutional neural network (CNN) for ASR
- Rapid adaptation of DNNs
- Parallel training of DNNs