YORK UNIVERSITÉ UNIVERSITY redefine THE POSSIBLE.

Why DNN Works for Acoustic Modeling in Speech Recognition?

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Outline

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redefine THE POSSIBLE.

- Introduction
- DNN/HMM for Speech
- Bottleneck Features
- Incoherent Training
- Conclusions
- Other DNN Projects

This talk is based on the following two papers:

[1] J. Pan, C. Liu, Z. Wang, Y. Hu and H. Jiang, ``Investigations of Deep Neural Networks for Large Vocabulary Continuous Speech Recognition", *Proc. of International Symposium on Chinese Spoken Language Processing (ISCSLP'2012)*, Hong Kong, December 2012.

[2] Y. Bao, H. Jiang, L. Dai, C. Liu, "Incoherent Training of Deep Neural Networks to De-correlated Bottleneck Features for Speech Recognition," submitted to 2013 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP'13), Vancouver, Canada.

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 → 100+ million free parameters

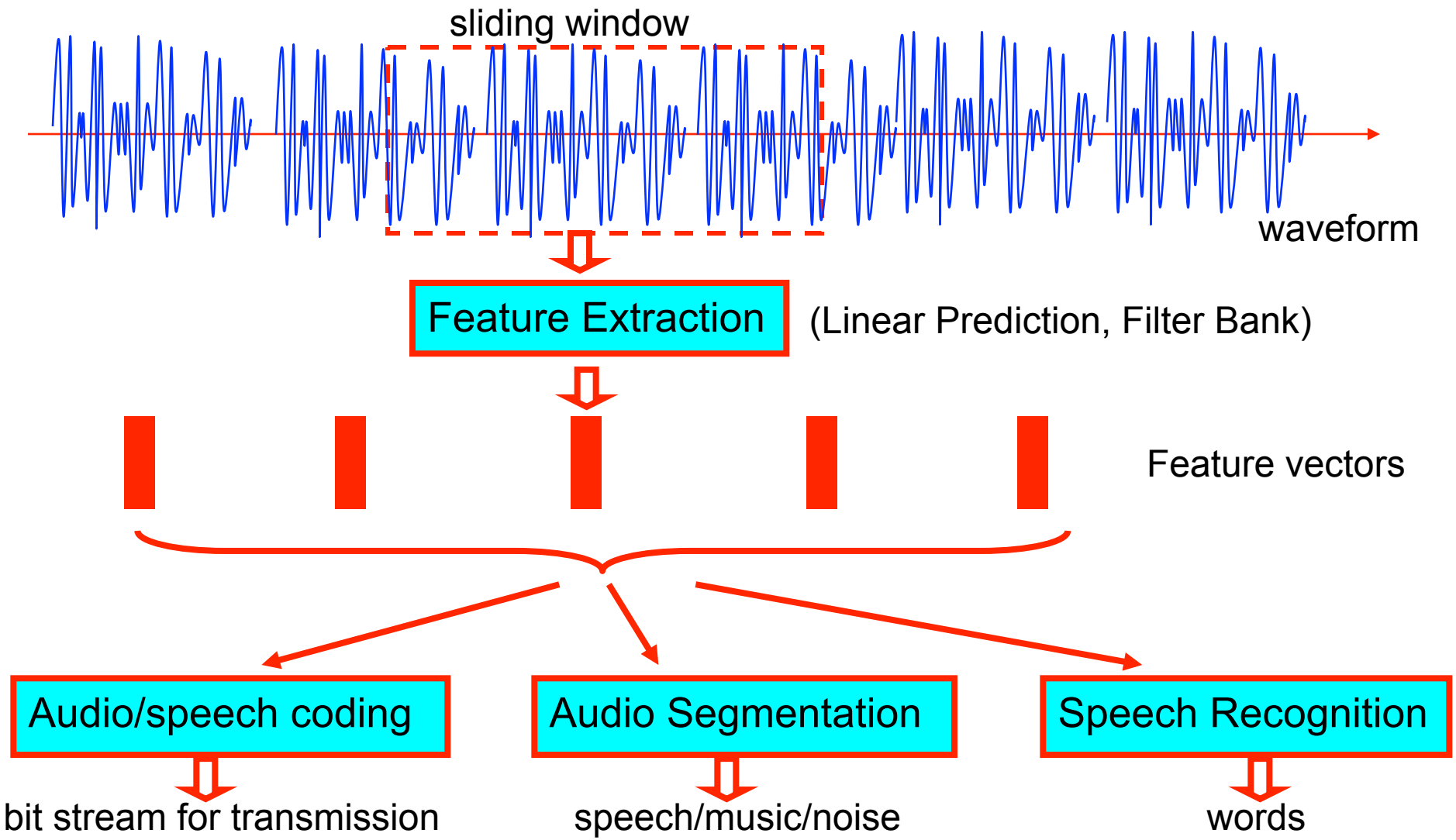
- Training Methods
  - Maximum Likelihood Estimation (MLE)
  - Discriminative Training (DT)

- Engineering Issues
  - Efficiency: feasible with 100-1000 of CPUs
  - Reliability: robust estimation of all parameters

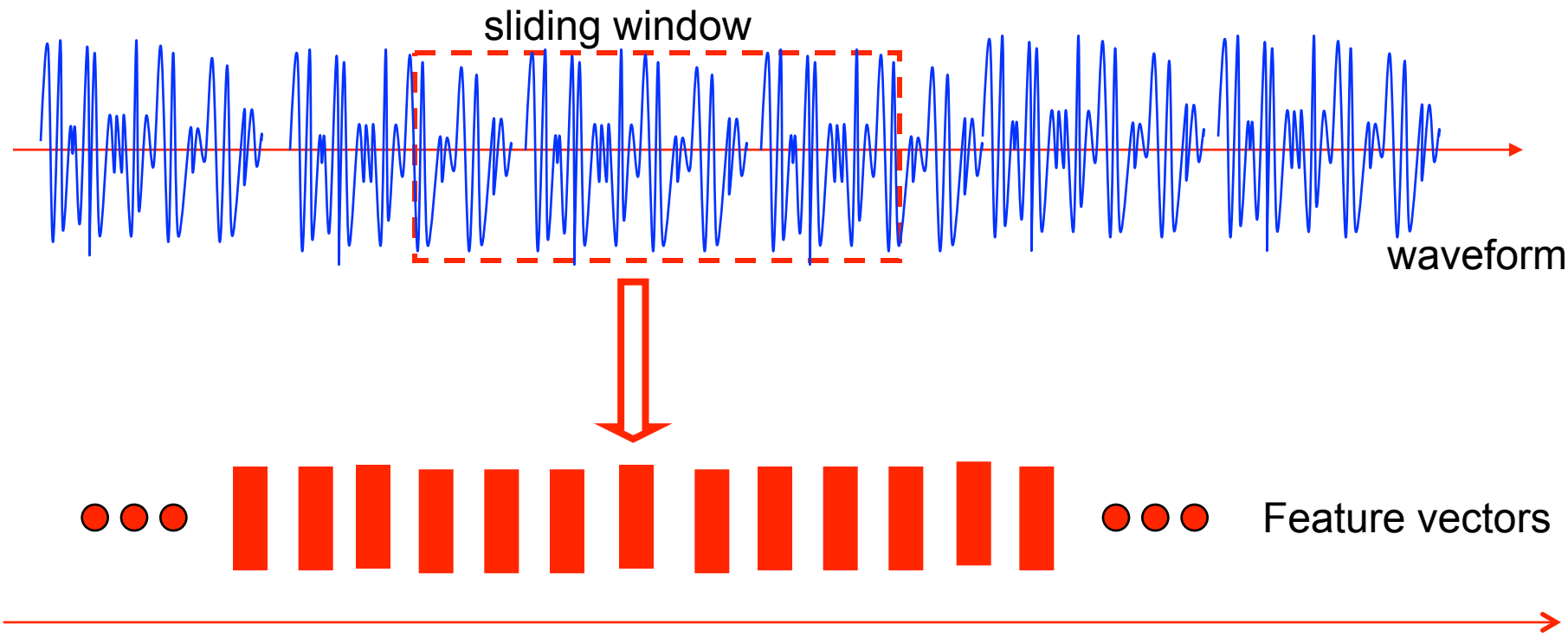
Neural Network for ASR

- **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, Yi, et al. 2010)*
- **2011: DNN for large-scale ASR**
  - **Over 30% rel. gain in Switchboard** *(Seide et al., 2011)*

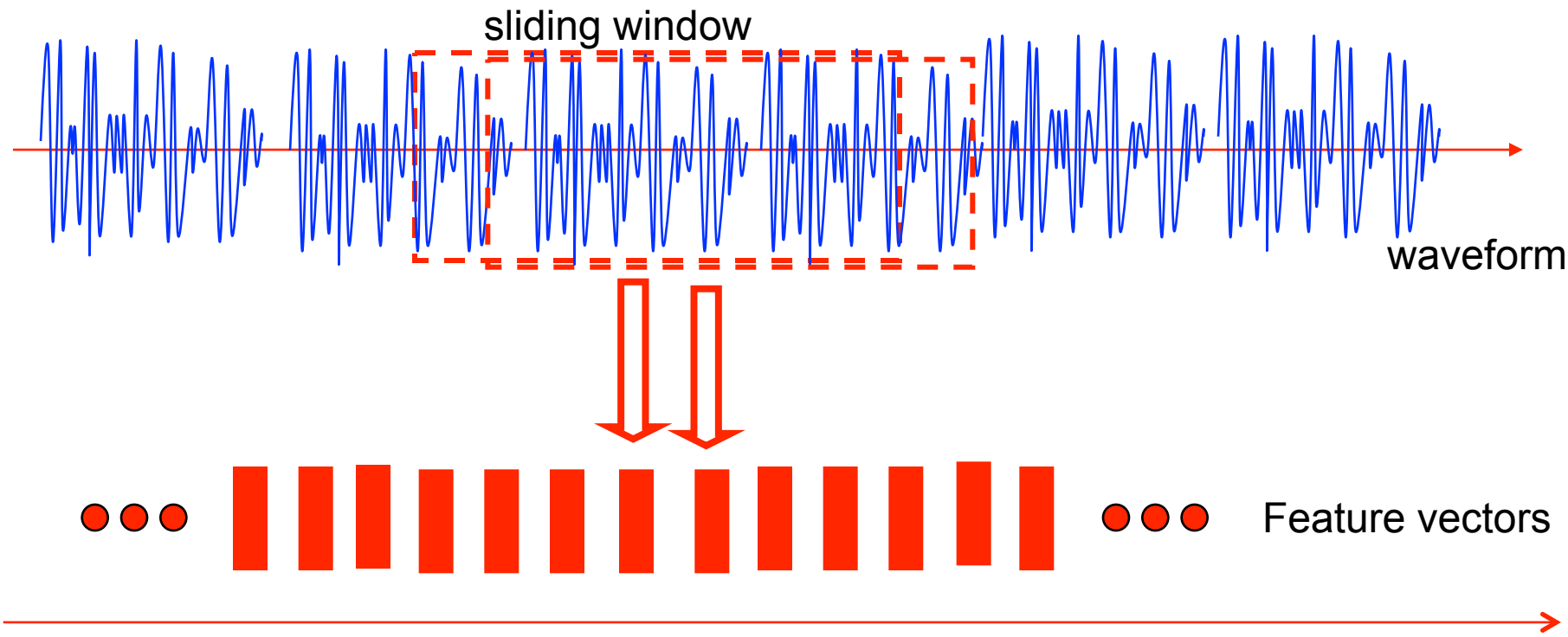
ASR Frontend



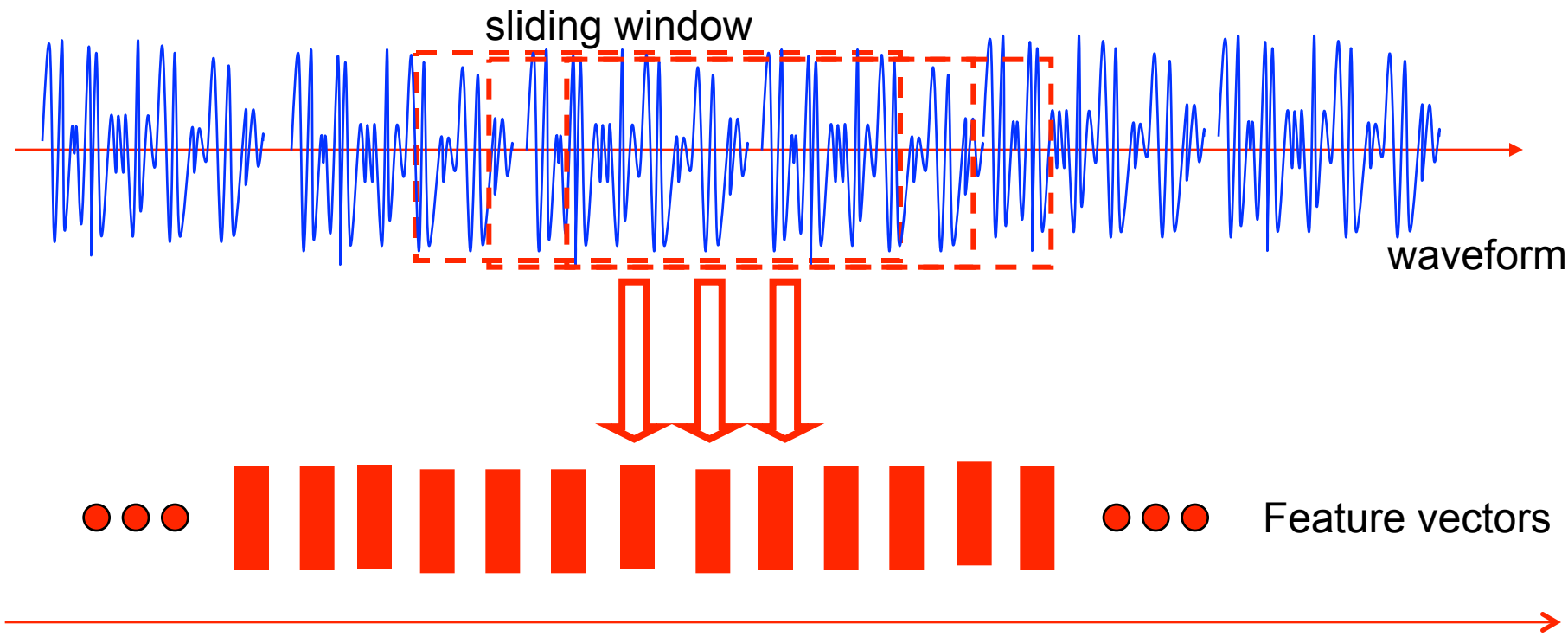
Short-time Analysis



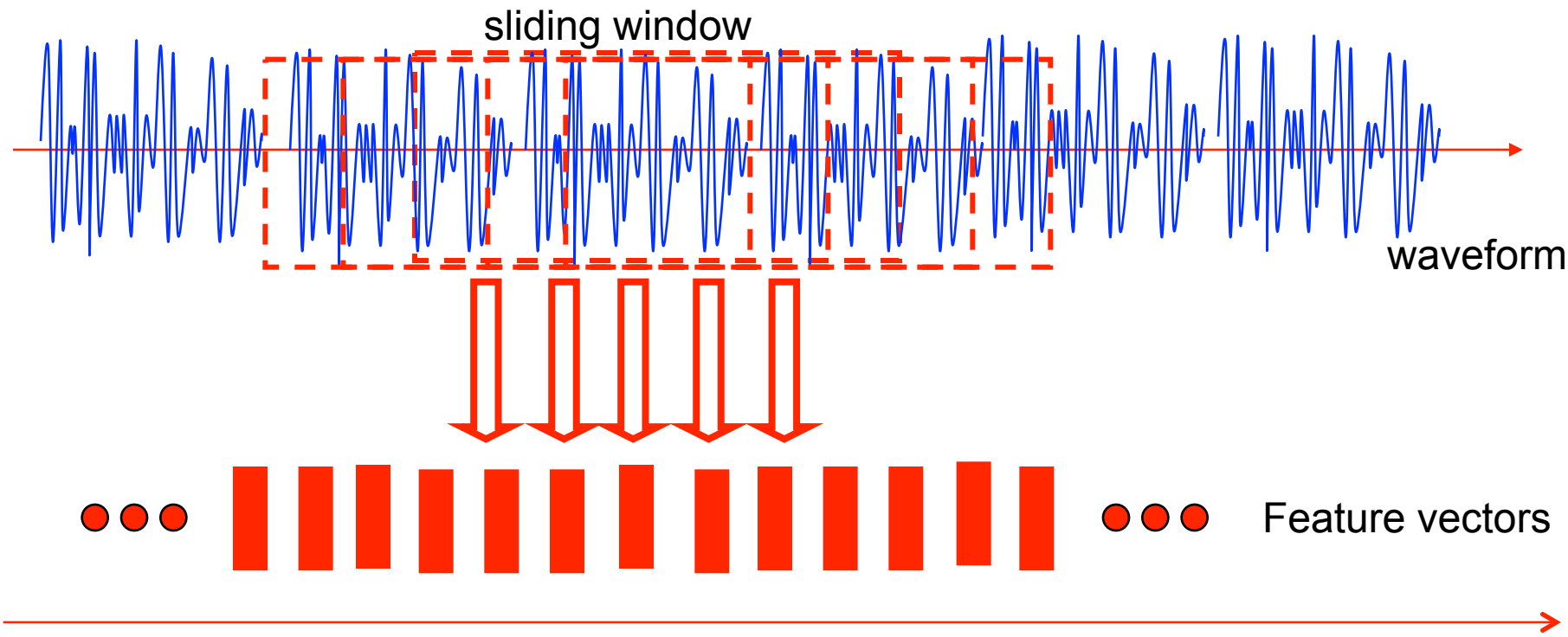
Short-time Analysis



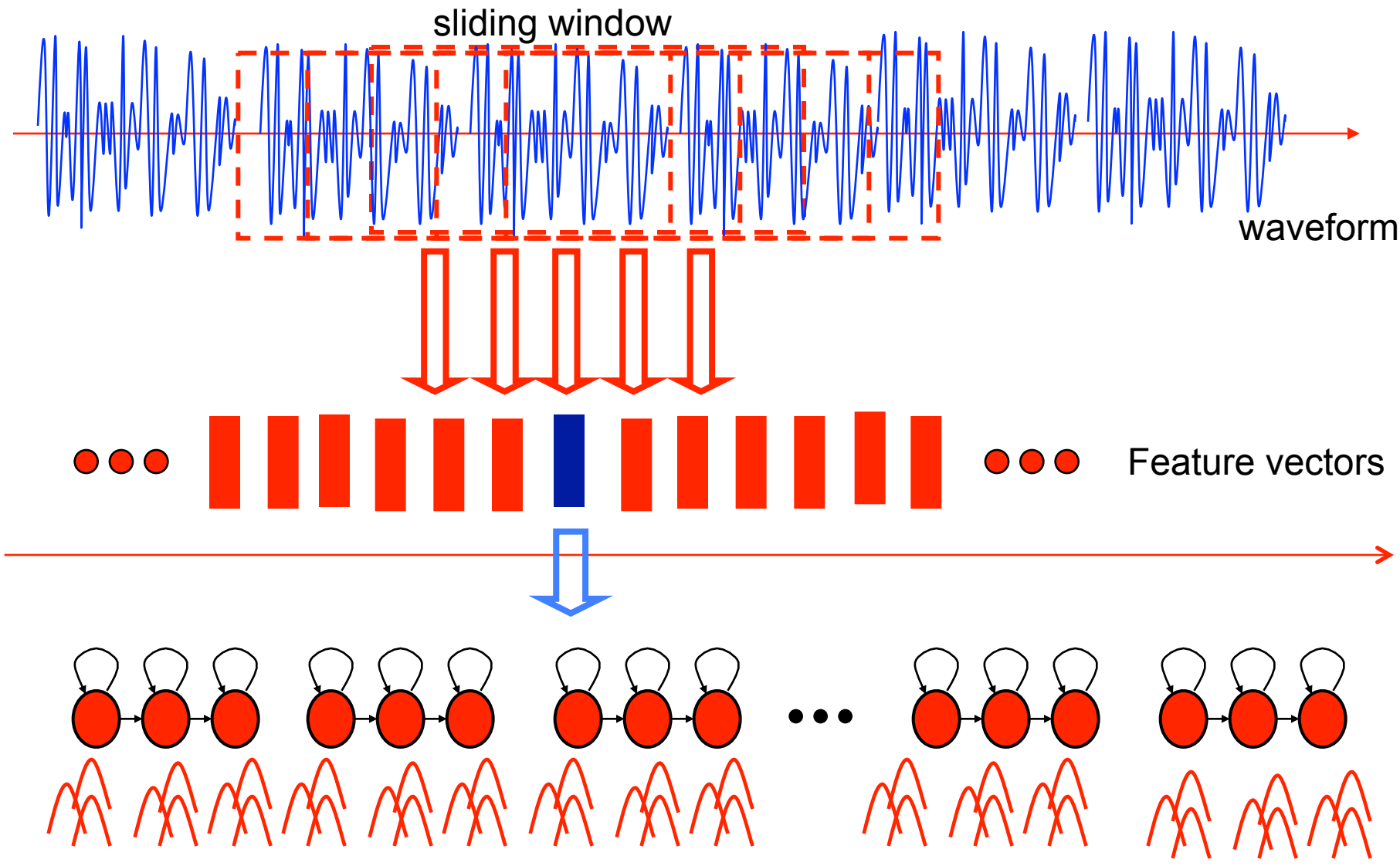
Short-time Analysis



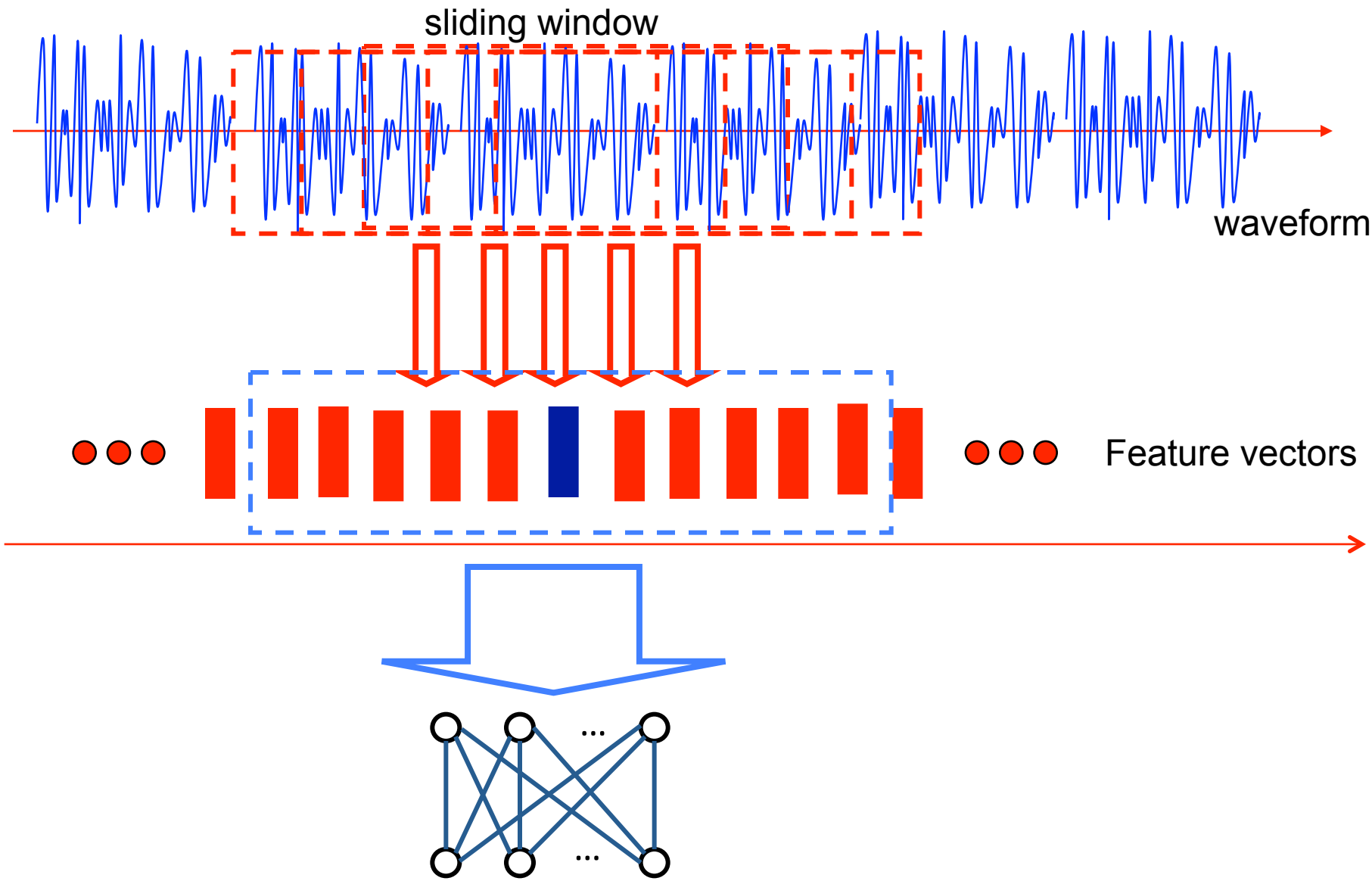
Short-time Analysis



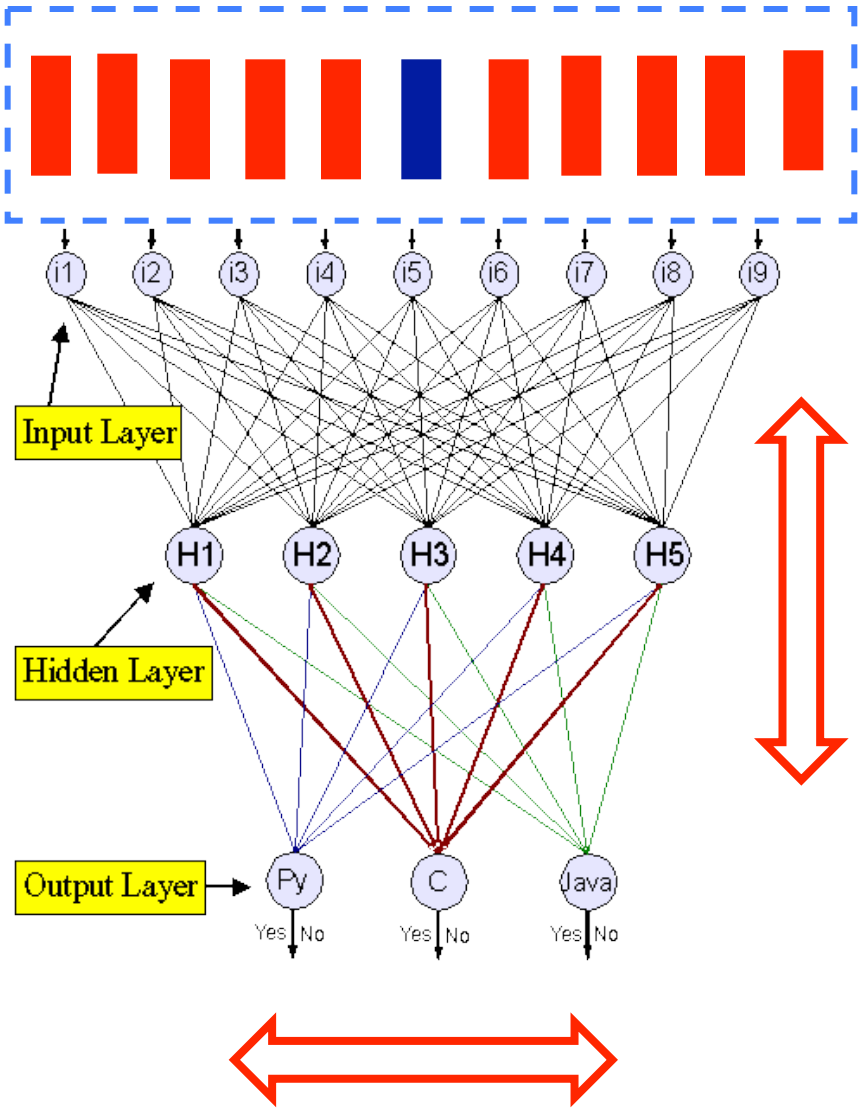
ASR Frontend: GMM/HMM



ASR Frontend: NN/HMM



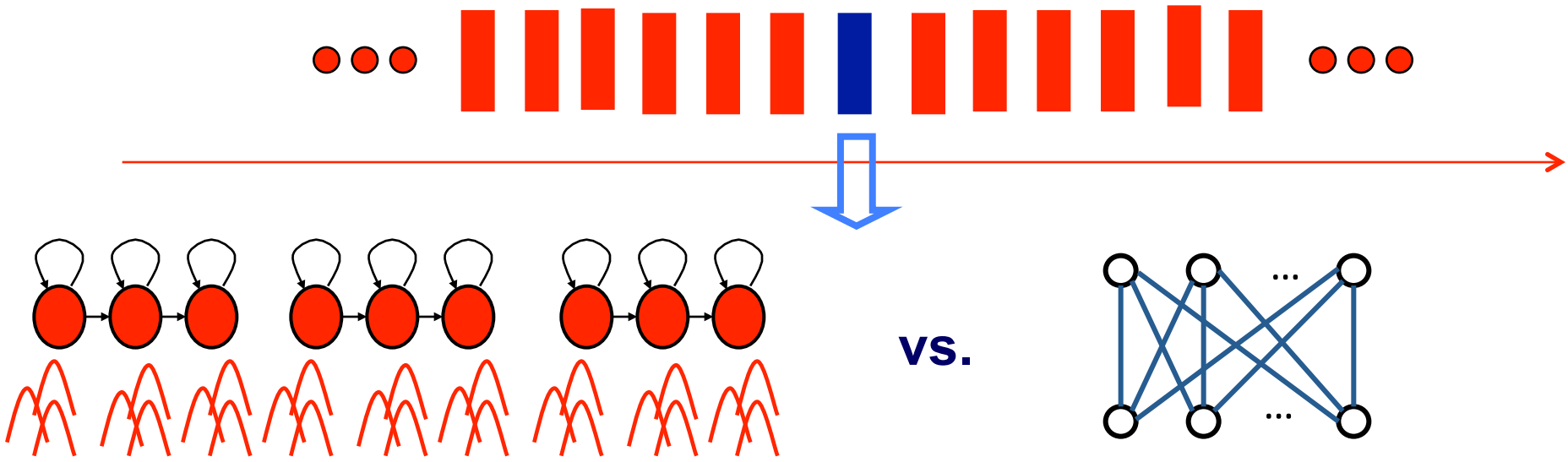
NN for ASR: old and new



- **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 → 2-10 k hours training data**

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

- 70-hour Chinese ASR task; 4000 tied HMM states
- GMM: 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

- 320-hour English Switchboard task; 9000 tied HMM states
- GMM: 40 Gaussian per state
- DNN: pre-trained; 2000 nodes per layer; 1-5 hidden layers

Numbers in word error rates (%)
NN-1: 1 hidden layer; DNN-3/5: 3/5 hidden layers
MPE GMM: discriminatively trained GMM/HMM

Context window		NN-1	DNN-3	DNN-5	MPE GMM
1	Hub98	44.8	43.9	42.6	43.4
	Hub01	35.4	34.8	33.1	32.8
11	Hub98	39.7	33.4	**31.2**	n/a
	Hub01	31.4	25.6	**23.7**	n/a

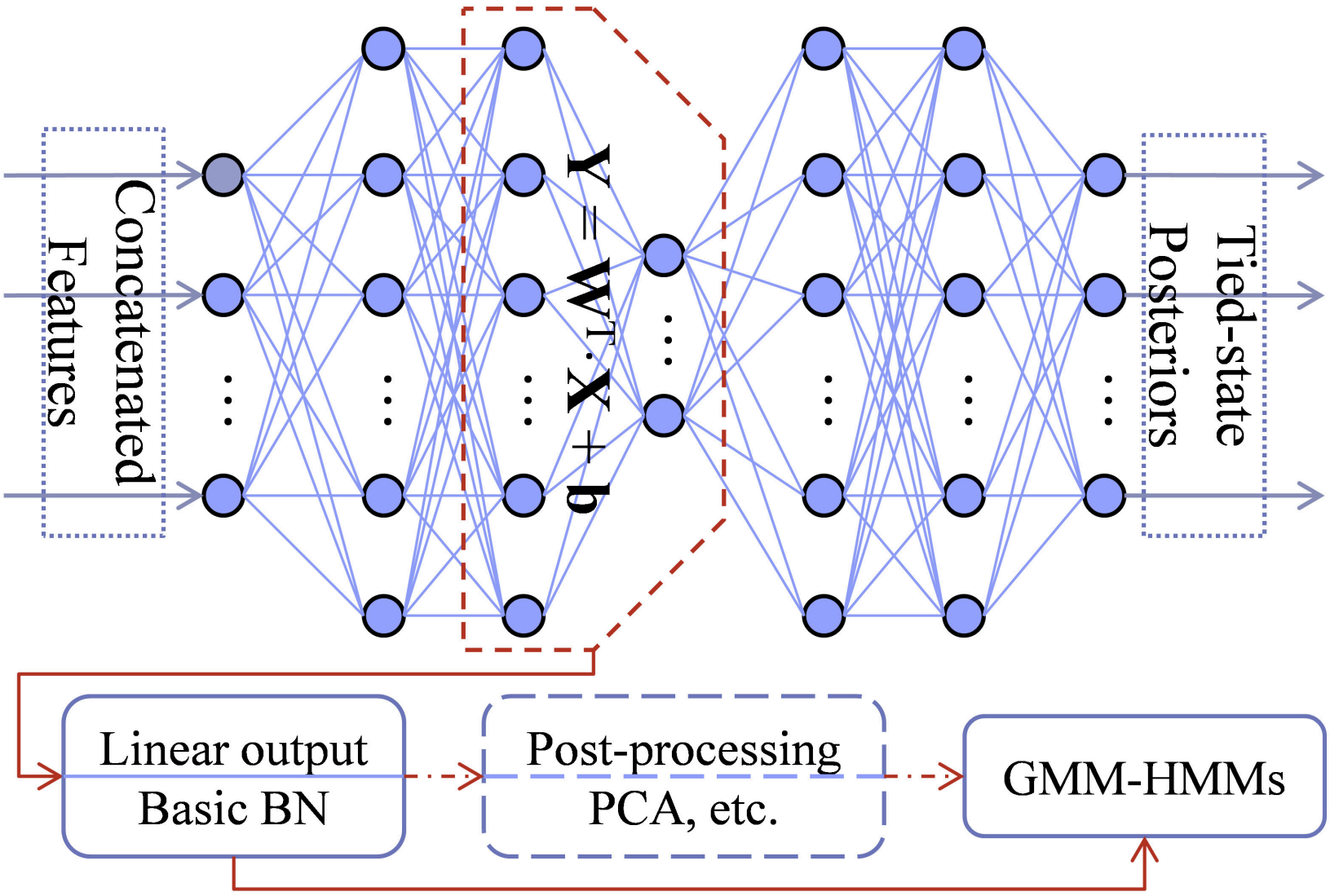
Conclusions (I)

- 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



Experiment (I): Bottleneck(BN) Features

70-hour Chinese ASR Task (word error rate in %)
MLE: maximum likelihood estimation
MPE: discriminative training

	MLE	MPE
GMM-HMM	18.2	**16.7**
CD-DNN-HMM	**13.1**	
BN-GMM-HMM	13.6	**12.2**

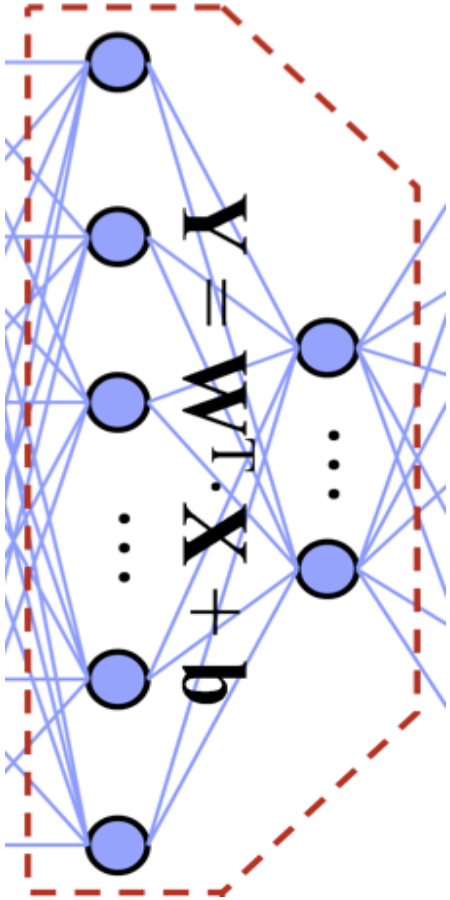
Experiment (II): Bottleneck Features (BN)

320-hour English Switchboard Task (word error rate in %)
MLE: maximum likelihood estimation
MPE: discriminative training

Acoustic Models	Hub5e98		Hub5e01	
	MLE	MPE	MLE	MPE
GMM-HMMs	46.6	**43.4**	35.4	**32.8**
CD-DNN-HMMs	**31.2**		**23.7**	
BN-GMM-HMMs	34.3	**31.3**	26.0	**23.2**

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:**

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

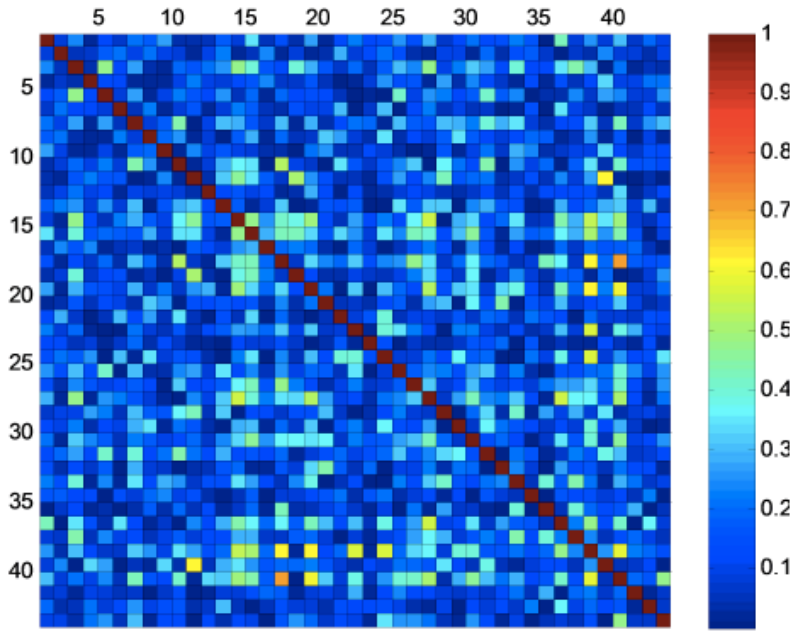
- **Derivatives of coherence:**

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

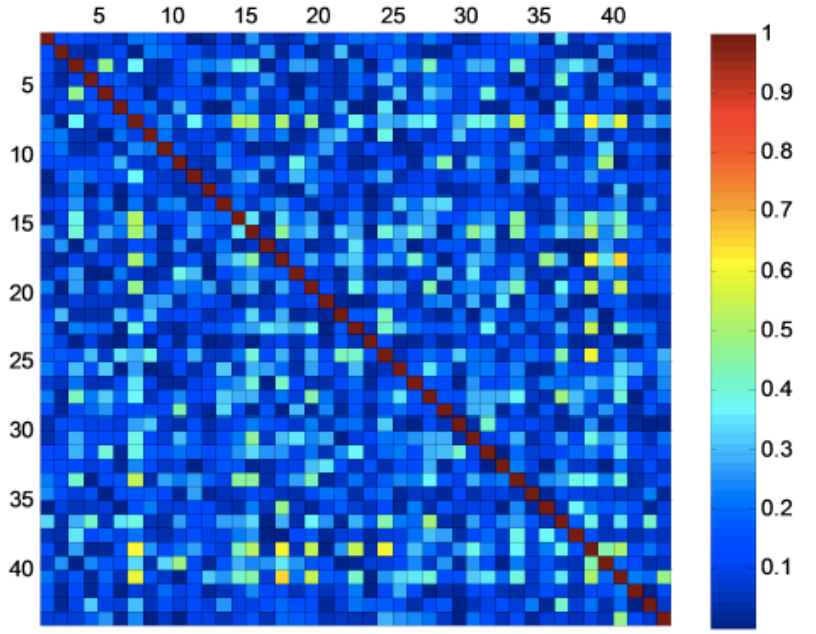
- **Back-propagation is still applicable…**

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:

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

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:**

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

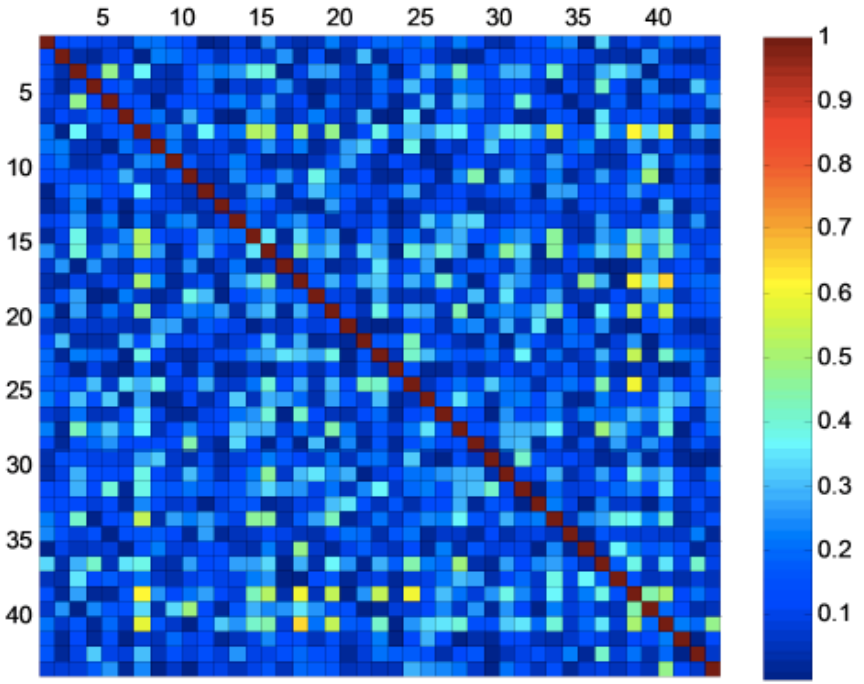
where

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

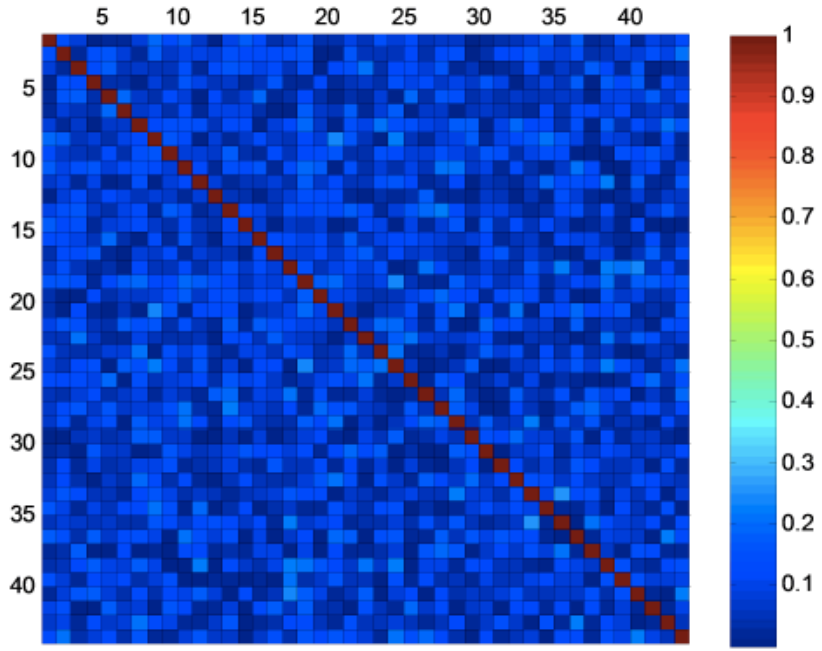
- **Back-propagation still applies except Cx is computed for each mini-batch**

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 (I): Incoherent Training

70-hour Chinese ASR Task (word error rate in %)
MLE: maximum likelihood estimation
MPE: discriminative training
DNN-HMM: 13.1%

	MLE	MPE
Baseline BN	13.6	**12.2**
Weight-matrix Incoherent BN	**13.3**	-
Mini-batch-data Incoherent BN	**13.2**	**12.0**

Experiment (II): Incoherent Training

320-hour English Switchboard Task (word error rate in %)
MLE: maximum likelihood estimation
MPE: discriminative training
DNN-HMM: 31.2% (Hub5e98) and 23.7% (Hub5e01)

BN Feature Systems	Hub5e98		Hub5e01	
	MLE	MPE	MLE	MPE
Baseline BN	34.3	31.3	26.0	23.2
Weight-matrix Incoherent BN	**34.0**	-	**25.7**	-
Mini-batch-data Incoherent BN	**33.8**	**31.0**	**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 works

- Apply incoherent training to general DNN learning
- Other nonlinear dimensional reduction methods for concatenated features